WPS5850

Policy Research Working Paper 5850

Vulnerability and Livelihoods before and after the Haiti Earthquake

Damien Échevin

The World Bank
Latin America and the Caribbean Region
Social Protection Sector
October 2011

Abstract

This paper examines the dynamics of poverty and vulnerability in Haiti using various data sets. As living conditions survey data are not comparable in this country, we first propose to use the three rounds of the Demographic Health Survey (DHS) available before the earthquake. Decomposing household assets changes into age and cohort effects, we use repeated cross-section data to identify and estimate the variance of shocks on assets and to simulate the probability of being poor in the future. Poverty and vulnerability profiles are drawn from these estimates. Second, we decompose vulnerability to poverty into various sources using a unique survey conducted in 2007 in rural areas. Using two-level modelling of consumption/income, we assess the impact of both observable and unobservable idiosyncratic and covariate shocks on households' economic well-being. Empirical findings show that idiosyncratic shocks, in particular health-related shocks, have larger impact on vulnerability to poverty than covariate shocks. Third, asset-wealth is characterized for households after the 2010 earthquake based on a survey designed to provide a rapid assessment of food insecurity in Haiti after the quake. Whereas it is not possible to confirm the existence of poverty trap, it seems that those households who have lost the most due to the earthquake succeeded in recovering more rapidly from the shock, regardless of the effects of assistance, and probably more in line with coping strategies that are specific to households.

This paper is a product of the Social Protection Sector, Latin America and the Caribbean Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at damien.echevin@usherbrooke.ca.

Vulnerability and Livelihoods before and after the Haiti Earthquake

Damien Échevin[1]

Keywords: Vulnerability; Poverty; Asset-Wealth; Earthquake; Haiti.

JEL Codes: D12; D31; I32; O15.

---

[1] Université de Sherbrooke. Email: damien.echevin@usherbrooke.ca. I gratefully acknowledge Andrea Borgarello, Carlo del Ninno, Nancy Gillespie, Francesca Lamanna, Philippe Leite, Ana Maria Oviedo and Ludovic Subran as well as participants at workshops in Port-au-Prince and Washington DC (World Bank) for their useful comments and suggestions. I also acknowledge Gary Mathieu from CNSA-Haiti for providing some of the data used in this paper. All errors and opinions expressed in this paper remain mine.

1. INTRODUCTION

Examining changes in poverty over time in Haiti poses severe challenges. An issue common to many developing countries is that survey data are not comparable. In Haiti, each of the three expenditure or income surveys collected in recent years (1986, 1999, and 2001) has a very different design. As a consequence, the analyses drawn on the basis of these surveys differ in the estimates of poverty incidence and trends (World Bank, 2006). The Demographic and Health Surveys (DHS), designed to be comparable, are of high quality but fail to include the expenditure or income data generally used for poverty estimates.

As reliable data are lacking in order to trace poverty and vulnerability trends over time, disparate views on the part played by reforms in alleviating ex ante or ex post poverty may arise. Indeed, the basic question of what has happened poverty- and vulnerability-wise over the last decade is far from having satisfactorily been answered. Addressing this issue is a pre-requisite to improving our understanding of the underlying social and economic processes that have contributed towards changes in economic well-being in Haiti. Some nationally representative household income and expenditure surveys have helped to provide a better understanding of living standards. In 1986, monetary poverty statistics (based on stated consumption expenditure) showed that 59.6% of Haitians were under the poverty line (Pedersen and Lockwood, 2001). This situation only slightly improved in 1999, as 48.0% were then categorized as poor. In 2001, the HLCS stated that 55.6% of households lived with less than US$1 per day and 76.7% with less than US$2 per day. This survey has not been conducted again since then.

In this paper, we explore different avenues in order to assess the dynamics of poverty in Haiti. First, we use the Demographic Health Surveys (DHS) to analyze the evolution of asset-poverty over time. We also propose a simple and intuitively appealing framework to assess vulnerability to asset-poverty with these data. Second, we characterize poverty and vulnerability in Haiti based on a unique survey conducted in 2007 in rural areas. Using two-level modeling of consumption/income, we assess the impact of both observable and unobservable idiosyncratic and covariate shocks on households' economic well-being. Third, we use a post-earthquake survey designed to provide a rapid assessment of food insecurity in Haiti in order to assess the post-earthquake dynamics of asset-poverty.

The paper is organized as follows. Section 2 gives a background concerning risks, poverty and coping strategies in Haiti. Section 3 examines the dynamics of poverty using pre-earthquake data. Section 4 provides a characterization of poverty and vulnerability in rural Haiti. In Section 5, post-earthquake distribution of household asset-wealth is in directly affected areas. The last section concludes.

2. BACKGROUND

Like most developing countries, Haiti faces insidious risks and shocks, including droughts, hurricanes, earthquake and economic and health shocks. The year 2008 proved particularly arduous for Haitians, as they simultaneously had to face a sharp rise in basic food and fuel prices, exceptionally bad weather conditions and a major decline in international trade due to the global economic crisis.

On January 12th, 2010, a magnitude 7.0 earthquake struck Haiti. It was the most powerful in over 200 years, causing thousands of Haitians to be killed, injured, homeless or displaced and inflicting tremendous infrastructural damage to the water and electricity infrastructure, roads and ports systems in the capital, Port-au-Prince, and its surrounding areas. What is more, although the hurricane season was not particularly destructive in 2010, Haiti was struck by a cholera epidemic in October. Until now, about 230,000 cases were reported, resulting in about 4,500 deaths. As of February 2011, about 3,000 patients per week were admitted for hospitalisation, as opposed to 10,000 at the November peak. USAID/OFDA believe that the disease will most likely be present in the country for the next years. Few months after the disaster, the human toll was extremely severe: 2.8 million people were affected by the earthquake, causing 222,570 deaths, and 300,572 injuries.[2,3] Over 97,000 houses were destroyed and over 188,000 were damaged. 661,000 people moved to non-affected regions.

Before the earthquake, poverty reaches very high levels in Haiti, with more than half of the population living in extreme poverty (i.e. with less than US$1 a day). Most of these approximately 4.5 million destitute lived in rural areas (about 70%) while the others lived in the metropolitan and other urban areas. Moreover, not only was extreme poverty widespread, but it was also severe. Income was among the most unequally distributed in the world: according to the 2001 Household Living Condition Survey, 20% of the poorest got 2% of total income while 20% of the richest got 68% of total income.

Multidimensional poverty was also far-reaching: social indicators such as literacy, life expectancy, infant mortality and child malnutrition showed that poverty was all-encompassing in Haiti. Around 4 out of 10 people could not read and write, nearly half of the population had no access to health care and more than four-fifths had no clean drinking water.[4] According to the 2009 national nutrition survey, chronic malnutrition (stunting) affected from 18.1% (Port au Prince) to 31.7% (Plateau Central) of 6-59 month old children. Chronic malnutrition had to be linked with low access to basic public services (health, education, running water, sanitation) and there was evidence that the extremely poor had much less access to services than their non-poor counterparts (World Bank, 2006). As a consequence, the under-five mortality rate was twice the regional average and life expectancy was about 18 years shorter than the regional average. Malnutrition also had to do with food insecurity in a country where food consumption was the main type of expenditure for Haitian households, so that they stood defenseless when faced with price fluctuations. In 2000, food consumption made up for 55.1% of the households' real consumption (IHSI, 2001), with stark contrasts between areas (64.2% in rural areas and 50.2% in urban ones). What is more, the food-dedicated budget coefficients were much higher for poorer households and also remained fairly high for richer rural households

[2] Source: United Nation Office for the Coordination of Humanitarian Affairs (OCHA).
[3] Kolbe et al. (2010) estimated that 158,679 people in Port-au-Prince died during the quake or in the six-week period afterwards owing to injuries or illness.
[4] According to the Household Living Conditions Survey (HLCS), 2001.

(about 50%). Among the factors fostering food insecurity, it should be noted that, on the one hand, a mere 10% of total consumption in rural areas in 1999-2000 came from subsistence economy, and that, on the other hand, an average 52% of the country's food availability came from imports: food imports currently made up for a quarter of total imports while they only used to represent 18.3% in 1981, and the value of the per capita food imports had sharply increased. Households being highly dependent on trade for food access issues, they had become highly exposed to price changes. Consequently, according to the comprehensive food security and vulnerability analysis (CFSVA)[5] that was conducted before the sharp inflation increase in 2007, 5.9% of rural households suffered from extreme levels of food insecurity while 19.1% of them were affected to a lesser extent by food insecurity.[6] In total, 25% of these households were in a situation of food insecurity in October 2007, that is, just before the price explosion in Haiti.

In order to cope with poverty and food insecurity, households adopt various strategies: they diversify their income sources, migrate or receive international remittances, adopt food restrictions strategies, lend money or food, sell part of the household's assets, or renounce costly activities (education for children, etc.). In Haiti, these strategies concern differently the poor and the rich: for instance, while remittances received from international migrants represented about 18 percent of Haiti's GDP in 2007, 72% of the richest households received emigrant remittances, as compared to only 39% for the poorest quintile.[7] On the other hand, food restriction strategies concerned 45% of poor rural households, who actually stated that they were used in cutting on quantities.[8] Food restrictions may induce early childhood malnutrition, with permanent cognitive and psychomotor consequences. Hence, malnutrition may induce direct productivity loss due to bad physical conditions, indirect productivity loss due to cognitive and education deficits, as well as loss due to increasing health care costs. For this reason, malnutrition lowers economic growth and perpetuates poverty, from mother to child (Alderman et al., 2002, Behrman et al., 2004). Other cut in expenditure such as taking children out of school can also have long-term effects on living standards.

3. DYNAMICS OF POVERTY BEFORE THE EARTHQUAKE

3.1.Data and Asset Index

Various indicators of well-being are generally used to measure poverty such as per capita household expenditures or per capita household income. However, in developing countries, good quality data on consumption or income prove to be hard to find in comparable surveys over time. Sahn and Stifel (2003) have listed several other problems in using household expenditures data such as measurement errors due to recall data or due to the lack of information concerning prices and deflators. Alternative measures of

[5] This study was a joint project of the World Food Program (WFP) and the National Coordination of Food Security Unit (NCFSU).
[6] CFSVA (2007). A score was calculated for food insecurity from data related to diet diversity on the one hand (based on the number of types of food or food groups eaten during the week previous to the survey), and to their consumption frequency expressed in number of days during the period of reference on the other hand.
[7] HLCS (2001).
[8] CFSVA (2007).

household's well-being such as the asset index should thus be considered.[9] Sahn and Stifel (2003) proposed to consider three categories of assets: household durables, housing quality and human capital.[10]

The absence of comparable data sources on income and expenditures over the last decade motivates our use of the Demographic and Health Surveys (DHS)[11] as an alternative instrument for assessing changes in poverty and vulnerability, relying on an asset index as an alternative metric of welfare. The DHS are provided at three periods in Haiti: 1995, 2000 and 2005. It is then possible to compare the assets over the three surveys.

Among household assets, we first consider liquid assets since these assets can be sold to purchase basic commodities in the event of a drop in income. Second, we consider more durable assets such as housing and education, which can also be accumulated in order to protect households against poverty. Other intangible assets such as household relations and social capital may have been taken into account in the analysis, but they are not available in the data.

The asset index is a composite indicator that is a linear combination of categorical variables obtained from a multiple correspondence analysis:[12]

$$a_i = \sum_{k=1}^{K} F_{1k} d_{ki} ,$$

where a_i is the value of the asset index for the ith observation, d_{ki} is the value of the kth dummy variable (with k=1,…,K) describing the asset variables considered in the analysis (liquid assets as well as housing variables and education of the head of the household), and F_{1k} is the value of the standardized factorial score coefficient (or asset index weights) of the first component of the analysis.[13] Built this way, the asset index can be described as the

9 See, for instance, Sahn and Stifel (2000), Filmer and Pritchett (2001), Sahn and Stifel (2003), Booysen et al. (2008).

10 This list of assets is not exhaustive and could be completed following Moser (1998)'s asset-based approach. In her asset vulnerability framework, Moser (1998) identifies several categories of assets and illustrates how portfolio management affects vulnerability. Asset management includes: labor (e.g., the number of earners in the family and their income level), human capital (education and health), productive assets (such as housing in urban areas or cattle in rural areas), household relations and social capital.

11 The DHS surveyed households in Haiti's nine departments. These departments were divided into 9 urban and 9 rural strata plus the metropolitan area of Port-au-Prince, amounting to a total of 19 strata. A two-stage sampling procedure was employed to select a representative sample of the target population. In the first stage, systematic sampling with probability proportional to the size of the strata was used to select 317 communities as clusters or primary sampling units (PSUs). In the second stage of sampling, households in each of the PSUs were systematically sampled.

12 See Benzécri (1973) or, more recently, Asselin (2009).

13 Alternatively, Sahn and Stifel (2000) used factor analysis, and Filmer and Pritchett (2001) used principal component analysis to measure their asset index. In reference to these methodologies, multiple correspondence analysis can be viewed as a principal component analysis applied to a contingency table with the chi2-metric being used on the row/column profiles, instead of the usual Euclidean metric. Multiple correspondence analysis provides information similar in nature to those produced by factor analysis and is less restrictive than principal component analysis.

best regressed latent variable on the K asset primary indicators, since no other explained variable is more informative (Asselin, 2009).

Next, the methodology is developed in order to compare distributions of the asset index over time. The data sets for several years are then pooled and asset weights are estimated using factor analysis for the pooled sample. We obtain:

$$a_{i(t)} = \sum_{k=1}^{K} F_{1k} d_{ki(t)}$$

where the factorial score coefficients F_{1k} are supposed to be constant over time.

Results from multiple correspondence analysis for pooled data sets (Demographic and Health Surveys 1995, 2000 and 2005) are presented in Table 1. Several wealth items have been used: liquid assets (radio, television, refrigerator, bicycle, motorcycle, car), housing characteristics (tap water, surface water, flush toilet, no toilet, electricity, rudimentary floor, finished floor) and head of household's education (no education, primary education, secondary education and tertiary education).

Table 1. Asset index weights for pooled data

Asset variables	Weights	% Inertia
Liquid assets		
Radio	0.310	2.1
Television	0.976	7.4
Refrigerator	1.146	4.5
Bicycle	0.462	1.4
Motocycle	0.807	0.6
Car	1.216	2.2
Housing		
Tap water	0.392	2.0
Surface water	-1.145	21.5
Flush toilet	1.150	2.6
No toilet	-1.076	19.7
Electricity	0.805	8.0
Rudimentary floor	-0.590	0.1
Finished floor	0.351	2.9
Head of household's education		
No education	-0.912	17.7
Primary education	-0.005	0.0
Secondary education	0.938	6.0
Tertiary education	1.309	1.5
Partial inertia		21.5

Source: Own computations using DHS 1995, 2000, 2005

Weights have signs consistent with interpretation of the first component as an asset-poverty index. Contribution of having no education appears to be particularly high (17.7%). Having no toilet also contributes in a large extent to inertia (19.7%). Having access to surface water contributes to 21.5% of inertia. Other items contribute to less than 10% of inertia.

3.2. Other Welfare Indices

Income Determination

Other indices than the asset index can be used in order to approximate well-being. Firstly, economists generally consider that total expenditure or income should be favoured. However, in developing countries, national surveys sometimes do not provide such information on households. It is even more difficult to get it on a regular basis.

Let us start with a log linear model of income determination:

$$\ln y_{i(t)t} = x'_{i(t)t}\,\beta_t + e_{i(t)t}$$

where $y_{i(t)t}$ is the income of household *i*(t) at time *t*, $x_{i(t)t}$ is a vector of explanatory variables and $e_{i(t)t}$ is an error term that is supposed to be independent and identically distributed. As proposed for instance by Stifel and Christiaensen (2007), it is possible to calculate $\ln y_{i(t+k)t+k} = x'_{i(t+k)t+k}\,\beta_{t+k} + e_{i(t+k)t+k}$, for all integers *k*, using estimates of $e_{i(t+k)t+k}$ and β_{t+k} drawn from the estimated distributions of $e_{i(t)t}$ and β_t obtained from the previous equation. In doing so, we suppose that β_{t+k} and β_t have the same distribution. This method is directly inspired from poverty mapping methodology (*cf*. Elbers et al., 2003). It is then possible to compare several predicted distributions of income over time even if these distributions are not observed in each time period. This is actually the case when using, on the one hand, the Household Living Conditions Survey (HLCS), which is the most recent national household survey, conducted in 2001 by the Haitian Statistical Office (IHSI), and which includes modules on income, health, education, and other household's assets; and, on the other hand, the Demographic Health Survey (DHS), a nationally representative household survey conducted every 5 years (1995, 2000, 2005) that provides data for a wide range of indicators in the areas of population, health, nutrition and other individual and household variables like assets and education. Finally, the combination of $\hat{e}_{i(t+k)t+k}$ and $\hat{\beta}_{t+k}$, along with the available variables $x_{i(t+k)t+k}$, yields :

$$\ln \hat{y}_{i(t+k)t+k} = x'_{i(t+k)t+k}\,\hat{\beta}_{t+k} + \hat{e}_{i(t+k)t+k}$$

Based on this model, we will use a simple way of predicting $\ln \hat{y}_{i(t+k)t+k}$ by using $x'_{i(t+k)t+k}\,\hat{\beta}_t$. However, we should recognize that this short cut of the model will result in an underestimate of the variance of the distribution of the predicted value of income.[14]

Health and Nutrition Index

Secondly, Sahn and Stifel (2002) suggest using a height-for-age z-score (HAZ-score) in order to approach well-being. This score can be stated as follows:

$$HAZ - score_i = \frac{H_i - H_{median}}{\sigma_H}$$

where H_i is height for child *i*, H_{median} is the median height for a healthy and well-nourished child from the reference population of the same age and gender and σ_H is the standard deviation from the mean of the reference population. By convention, a child whose HAZ-score falls below -2 is classified as malnourished (stunting). Note that in the health and nutrition literature the HAZ-score is generally considered as a reliable indicator of chronic malnutrition. This score in Haiti is relatively high, with about one child under 5 years old out of four being concerned by stunting or chronic malnutrition.

To go one step further, in order to determine the health and nutritional status of children, we consider a health production function:

$$h_{it} = h(x_{it}, Z_{it}, C_{it}, u_{it})$$

where x_{it} is consumption, Z_{it} is a vector of household and individual characteristics, C_{it} is a vector of community-level characteristics, and u_{it} is unobserved heterogeneity. To apply this model empirically, we use the HAZ-score for h_{it} and, in the absence of data concerning consumption, we will use predicted income or asset index as proxies for x_{it}. Note that the continuous index h_{it} can also be considered as a latent variable, since we could class the children into two groups: one group whose HAZ-score is below -2 and one whose HAZ-score is above -2, with -2 being the malnutrition poverty threshold.

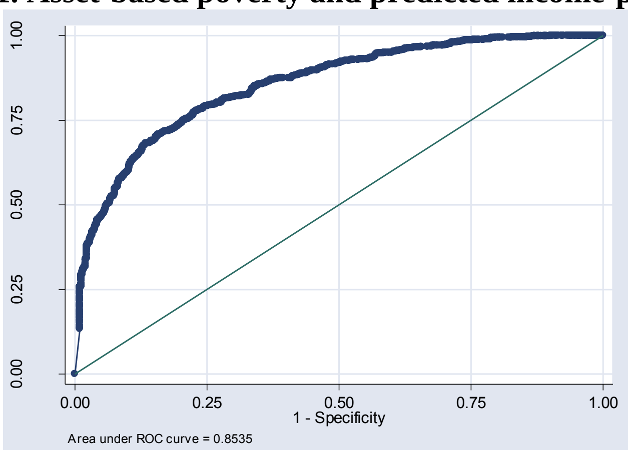
[14] Note that one important drawback of the methodology concerns the calculation of standard errors of the estimates (Tarozzi and Deaton, 2009). Indeed, although the methodology has been forcefully advocated and considerably enhanced by Elbers et al. (2003), it is still criticized, in particular because it relies on assumptions that are virtually untestable. This approach has for instance been used by the World Bank (2006) to compare welfare over time in Haiti. The estimates show a small decline in extreme poverty over time nationally, from 60% in 1986 to 54% in 2001. Estimates based on the US$2-a-day poverty line show trends broadly similar to those for US$1-a-day poverty rates. The US$2-a-day headcount estimates show a decline from 84% to 78%. However, given the large margin of error in the estimates, the change has not been proved to be statistically significant.

3.3.Validation of the Asset Index

We examine to what extent the asset index overlaps with other indices, i.e. the extent to which one acts as an indicator for the other. One possible way of examining this is to define a poverty threshold for predicted income and one for assets. The proportion of people classified as poor under both thresholds can then be examined and compared with those classified as poor under only one threshold and with those not classified as poor under either threshold. However, the results yielded may be sensitive to the threshold that was selected. Alternatively, the receiver operating characteristic (ROC) curve provides a useful procedure for this comparison. It is arguable that the area under the ROC curve gives a more intuitive summary of the extent to which two dimensions of welfare are correlated in the sense of identifying the poor. Figure 1 suggests that asset-based poverty is a good indicator of income-poverty (when using predicted income as a proxy for well-being). With an area below the ROC curve of around 0.85, this suggests that targeting low-asset households is going to alleviate much of (though not all) poverty as measured with the predicted income, and vice-versa.

The ROC curve methodology states as follows. Let us consider income-poor households that are below a certain threshold (that is, US$2 when considering poverty and US$1 when considering extreme poverty). If the asset index assigns someone as poor who is also poor under the income-poverty definition then this is called a "true positive" (TP), also called "sensitivity." If it signals as poor someone who is not poor under the income definition, it is a "false positive" (FP), also called "(1 – specificity)," which is also known as a type I error (i.e. poor people classified as non-poor). If it signals someone as non-poor even though this person is poor under the income definition, it is a "false negative" (FN). Finally "true negatives" (TN) are those who are classified as non-poor under both definitions.

Figure 1. Asset-based poverty and predicted income-poverty



Source: Own computations using HLCS 2001 and DHS 2005

Table 2 summarizes the results together with Spearman rank correlations between HAZ-score and alternative measures of well-being. As for the area under the ROC curve, it is difficult to settle, from this analysis, on which of these two indices is the best predictor for the health and nutrition welfare index. Indeed, they seem to have comparable power in targeting chronically malnourished children.

Table 2. Correlations between HAZ-score and alternative measures of well-being

	Predicted income	Asset index
Area under ROC curve	0.6087	0.6002
	0.6521	**0.6415**
Spearman rank correlation	0.2133	0.1879
	0.2606	**0.2230**

Source: Own computations using HLCS 2001 and DHS 2000 (2005 in bold)

In a last analysis of correspondence between welfare indices, we use the methodology proposed by Sahn and Stifel (2003). In order to assess the explanatory power of the asset index and the predicted income in predicting well-being, separate models of health and nutritional status are estimated conditioned on (i) the log of predicted per capita household income, (ii) the log of household asset index, (iii) both the log of predicted per capital household income and the log of household asset index. The probit regression model is fitted using an indicator whose value is one when the child is malnourished (HAZ-score under -2) and zero otherwise. Once the models are run, we use them to predict child HAZ-scores and compare the rank correlations and ROC curves between the fitted nutritional outcomes and the actual measured outcomes.

Table 3. Probit estimates

HAZ-score	Predicted income only (i)		Asset index only (ii)		Predicted income & Asset index (iii)			
Elasticity	-0.3304	**-0.3778**	-0.2895	**-0.3424**	-0.2158	**-0.2177**	-0.1879	**-0.2416**
z-statistic	-8.38	**-6.37**	-8.96	**-7.53**	-5.03	**-3.50**	-5.01	**-4.61**
Pseudo R2	0.0334	**0.0539**	0.0327	**0.0552**		0.0367	**0.0598**	

Source: Own computations using HLCS 2001 and DHS 2000 (2005 in bold)

Table 3 shows that the pseudo R-square is approximately the same for the model with asset index and for the model with predicted income: it is slightly higher in 2005 for the former. Looking at the measures of correlations between actual and fitted values of the health and nutrition index in Table 4 shows that fitted values are better correlated to actual values when asset index is used as a regressor. Using both indices in a regression does not significantly improve the correlations. In conclusion, these findings suggest that analysts are not worse off, and may be better off, conditioning child nutrition models on the asset index rather than predicted income in their effort to predict nutritional outcomes and target programs.

Table 4. Correlations between actual and fitted HAZ-score

Actual HAZ-score	Fitted HAZ-score *with* Predicted income only (i)	Asset index only (ii)	Predicted income and asset index (iii)
Area under ROC curve	0.5978	0.5985	0.6033
	0.6627	**0.6669**	**0.6730**
Spearman rank correlation	0.1889	0.1861	0.1981
	0.2551	**0.2496**	**0.2652**

Source: Own computations using HLCS 2001 and DHS 2000 (2005 in bold)

3.4. Evolution of Asset-Poverty over Time

For the purpose of the temporal comparison of assets, all of the household asset indices used in the analysis are calculated on an individual basis by dividing indices by household size. In order to factor in asset-related economies of scale within the household, indices were also calculated on a per household basis and for assets divided by the square root of household size. Results did not qualitatively change with the use of these different definitions of asset indices, so that they prove to be robust to the choice of equivalent scales. Asset-based poverty headcount (P0), poverty gap (P1), and poverty severity (P2) indices are presented in table 5 for various thresholds. The asset-based poverty lines are the 20th, 40th, 60th and 80th percentiles of the 1995 distribution of the asset index. In Table 5, results have been split according to a rural/urban division so that the evolution of the index can be observed in different areas. It appears that asset-based poverty decreased between 1995 and 2000 and remained fairly constant between 2000 and 2005. Moreover, it mainly declined in the North-East, Artibonite, Centre, and Grand'Anse departments, especially in rural areas.[15] These trends are comparable to those observed from chronic malnutrition rates, which have also decreased over time from 32% in 1995 to 23% in 2000 and 24% in 2005.

Table 5. Changes in asset-based poverty between 1995 and 2005

		Poverty headcount (P0)			Poverty gap (P1)			Poverty severity (P2)		
Percentile		1995	2000	2005	1995	2000	2005	1995	2000	2005
20th	National	0.20	0.15	0.17	0.139	0.111	0.125	0.1175	0.0966	0.1088
	Urban	0.01	0.01	0.02	0.007	0.004	0.009	0.0052	0.0030	0.0066
	Rural	0.31	0.23	0.28	0.214	0.172	0.201	0.1811	0.1499	0.1762
40th	National	0.40	0.31	0.34	0.258	0.198	0.221	0.2068	0.1586	0.1797
	Urban	0.06	0.02	0.06	0.026	0.011	0.028	0.0165	0.0072	0.0195
	Rural	0.59	0.48	0.53	0.389	0.304	0.348	0.3145	0.2446	0.2854
60th	National	0.60	0.52	0.51	0.378	0.305	0.323	0.2951	0.2311	0.2524
	Urban	0.21	0.14	0.18	0.072	0.038	0.066	0.0399	0.0187	0.0394
	Rural	0.82	0.74	0.73	0.552	0.456	0.492	0.4395	0.3518	0.3930
80th	National	0.80	0.75	0.71	0.520	0.450	0.450	0.4064	0.3367	0.3491
	Urban	0.56	0.46	0.45	0.206	0.151	0.172	0.1082	0.0701	0.0952
	Rural	0.94	0.91	0.89	0.698	0.620	0.634	0.5751	0.4882	0.5166

Source: Own computations using DHS 1995, 2000, 2005

[15] These results are not reported here but are available upon request.

Aggregate changes in asset-based poverty follow from the relative gains or losses of the poor and vulnerable within specific sectors or groups as opposed to population shifts between these groups (Ravallion and Huppi, 1991, Sahn and Stifel, 2000). A methodology of decomposition of the change in asset-poverty can be stated as follows. Let us consider P a poverty measure for two distributions at time t and τ, and two sectors u (urban area) and r (rural area), so that:

$$P^t - P^\tau = (P_u^t - P_u^\tau)n_u^\tau + (P_r^t - P_r^\tau)n_r^\tau + \sum_{j=u}^{r}(n_j^t - n_j^\tau)P_j^\tau + \sum_{j=u}^{r}(P_j^t - P_j^\tau)(n_j^t - n_j^\tau).$$

The first two components are the within components: they show how asset-poverty in each of the residence areas (urban and rural) contribute to the aggregate change of asset-poverty between t and τ. The third component is the between component: it is the contribution of changes in the distribution of the population across two groups. The final component is a residual component that is a measure of correlation between population shifts and changes in asset-poverty within the groups.

Table 6 presents the decomposition of the change of the asset-based index headcount ratio between 1995 and 2005. This decomposition suggests that intra-rural effects account for most of the changes when the poverty line is chosen under the 80th percentile. Migration explains about 25% of the change and its contribution to the change generally declines when the poverty line gets higher. Finally, the contribution of declining asset-poverty in urban areas is low for low poverty lines and reaches nearly half of the change when the poverty line is fixed at the level of the 1995 80th percentile.

Table 6. Decomposition of changes in asset-based poverty between 1995 and 2005

	Headcount			Decomposition			
Poverty line				(Within)		(Between)	(Interaction)
(percentile in 1995)	1995	2005	Change	Urban	Rural	Migration	Crossed effect
20th	0.201	0.172	-0.028	0.016	-0.021	-0.011	0.003
40th	0.400	0.339	-0.062	-0.002	-0.043	-0.019	0.002
60th	0.600	0.513	-0.088	-0.011	-0.056	-0.022	0.002
80th	0.800	0.711	-0.089	-0.041	-0.032	-0.014	-0.002

Source: Own computations using DHS 1995, 2005

Other decompositions of the change in asset-poverty can be achieved by splitting the population into different groups of households according to education and gender of the head of household, and according to the presence of children under 5 years old in the household (see Table 7). It appears that the no or primary education group accounts for most of the change in asset-poverty, all the more so as lower asset-poverty line is chosen. The same statement can be made for households with male head or with under 5 children: households with these characteristics experienced a larger decrease in asset-poverty between 1995 and 2005. As a result of this analysis, we should emphasize that households with higher probability of being poor may have experienced a sharper decrease of asset-poverty over the last decade. This should thus be kept in mind when analyzing poverty in a more static manner.

3.1.Measuring Vulnerability[16]

Asset Based Approach

There are several arguments in favour of an asset-based approach to vulnerability. Firstly, since vulnerability is a dynamic concept, we can consider that consumption-poverty or income-poverty measurements, because they are static, are of limited use in capturing complex external factors affecting the poor as well as their response to economic difficulty (Moser, 1998). Secondly, owning assets reduces the risk for households to fall into poverty as a result of macroeconomic volatility (de Ferranti et al., 2000). Hence, accumulating assets—be they liquid or not (e.g., durable goods and housing), material or not (by fostering education, health, family and social networks)—helps people to insure themselves against falling into poverty and to cope with risks and shocks. Asset accumulation should thus be considered as a major factor in risk management.

Nevertheless, though an asset index can be a good proxy for living standards in order to measure poverty[17], two problems arise when using household wealth as an indicator of well-being in order to measure vulnerability to poverty. On the one hand, if assets are used for consumption-smoothing, then an asset-based approach overestimates vulnerability since assets can fluctuate whereas consumption does not. On the other hand, if assets are not used to smooth consumption, the approach would underestimate vulnerability. So, knowing whether an asset-based approach deviates from a more standard consumption-based approach is mainly an empirical question.[18]

Besides, we could ask whether, in some circumstances, an asset-based approach is not preferable when it comes to measuring vulnerability. Indeed, let us consider the most interesting and realistic case where productive assets contribute towards the income generation process and can also serve as buffer-stock in order to face a non-anticipated drop in income (Deaton, 1991, Carroll, 1992). Empirically though, many studies find little evidence supporting the buffer-stock hypothesis in developing countries.[19] For instance, Dercon (1998) shows that, given subsistence constraints and agent heterogeneity, rich households will accumulate assets more quickly than poor ones who will pursue low-risk, low-return activities. Interestingly enough, the evidence suggests that households with lower endowments are less likely to own cattle and returns to their endowments are lower. So, in presence of imperfect markets for credit and insurance, few households are able to smooth their consumption. What is more, when assets are mainly made up of productive assets, selling these assets would induce a permanent loss in income for the household who

[16] See Echevin (2010a) for a more complete version of this section and application to other countries.
[17] Sahn and Stifel (2003) show that an asset index obtained from a factor analysis on household assets using multipurpose surveys from several developing countries is a valid predictor of child health and nutrition and, thus, long term poverty.
[18] Echevin (2010a) provides such empirical evidence using Ghana Living Standard Surveys.
[19] See, among others, Rosenzweig and Wolpin (1993), Morduch (1995), Fafchamps et al. (1998), Kazianga and Udry (2006), and Hoddinott (2006).

could then fall into a poverty trap.[20] For this reason, poor households will prefer to smooth their assets instead of smoothing their consumption.[21]

An asset-smoothing behaviour might be a desirable strategy for households to avoid falling into poverty traps. As pointed out by Zimmerman and Carter (2003) who build on Dercon (1998)'s approach by incorporating the role of endogenous asset price risks, portfolio strategies can bifurcate between rich and poor households. In this setting, poor agents respond to shocks by using consumption to buffer assets when they get close to a critical asset threshold.[22]

Econometric Framework

Let us quantify vulnerability to poverty by considering the probability to be poor in the future that is having predicted future income or assets below a pre-defined threshold, conditional on household characteristics and exogenous shocks. This probability can be stated as follows:

$$\hat{v}_{it}^{c} = \Pr(a_{it+1}^{c} < z \mid x_{it}^{c}, x_{it+1}^{c}, a_{it+1}^{c}),$$

where a_{it+1} is household *i* welfare (using per capita asset index as a proxy) at time *t+1*, x_{it} and x_{it+1} are vectors of household characteristics at time *t* and *t+1* respectively that are not used in the definition of cohort *c*, and *z* is a given threshold. This probability is modelled using pseudo panel data. Indeed, in the absence of panel data, repeated cross-section data can be grouped together by age cohort, education, and geographic groups in order to implement the methodology. So, the welfare index can be modelled in logarithm as follows:[23]

$$\ln a_{it}^{c} = x_{it}^{c}\beta_{t}^{c} + \eta_{it}^{c},$$

where superscript *c* denotes cohort group. It is assumed that the residual term η_{it}^{c} can be decomposed into an individual specific effect α_{i}^{c} and an error term ξ_{it}^{c} as follows:

$$\eta_{it}^{c} = \alpha_{i}^{c} + \xi_{it}^{c},$$

[20] Zimmerman and Carter (2003) and Carter and Barrett (2006), among others, have analyzed the existence of poverty traps when households are involved in various asset accumulation dynamics.

[21] Note that if households are able to diversify their portfolio of assets into risky and safe assets, then in presence of credit constraints they will choose to lower the proportion of risky assets held in order to smooth income over time (Morduch, 1994).

[22] The empirical evidence concerning the existence of such asset-poverty traps and thresholds are mixed with some authors finding evidence of its existence: see, for instance, Lybbert et al. (2004), Adato et al. (2006), Barret et al. (2006) or Carter et al. (2007). Carter and May (1999, 2001) also provide evidence of poverty traps although they are differently theoretically grounded.

[23] Bourguignon and Goh (2004) proposed a similar method for assessing vulnerability to poverty, although relying on earning dynamics.

where α_i^c can be modelled either as a fixed effect or as a random effect and ξ_{it}^c is supposed to follow a martingale that is

$$\xi_{it}^c = \xi_{it-1}^c + \varepsilon_{it}^c,$$

with ε_{it}^c denoting an innovation term that is supposed to be normally, independently and identically distributed, with mean zero and variance $\sigma_{\varepsilon ct}^2$. Grouping households together by cohorts gives the possibility to estimate the model with repeated cross-section surveys. Estimating this model by focusing on second-order moments—as in Deaton and Paxson (1994)—yields estimates of $\sigma_{\varepsilon ct+1}^2$ that can directly be used to predict the degree of household vulnerability in cohort *c*. Indeed, by first drawing a value $\tilde{\varepsilon}_{it+1}^c$ in the normal distribution with mean zero and variance $\hat{\sigma}_{\varepsilon ct+1}^2$, we obtain the probability to become poor in *t+1* for household *i* in cohort *c*:

$$\hat{v}_{it}^c = \Pr(a_{it+1}^c < z \mid x_{it}^c, x_{it+1}^c, a_{it+1}^c) = \Phi\left(\frac{\ln z - x_{it+1}^c \hat{\beta}_{t+1}^c - \ln a_{it}^c + x_{it}^c \hat{\beta}_t^c - \tilde{\varepsilon}_{it+1}^c}{\hat{\sigma}_{\varepsilon ct+1}}\right),$$

where $\Phi(.)$ denotes the cumulative density of the standard normal distribution. Assuming, for simplicity sake, that $x_{it+1}^c \hat{\beta}_{t+1}^c = x_{it}^c \hat{\beta}_t^c$ gives $\hat{v}_{it}^c = \Pr(a_{it+1}^c < z \mid x_{it}^c, x_{it+1}^c, a_{it+1}^c) = \Phi\left(\frac{\ln z - \ln a_{it}^c - \tilde{\varepsilon}_{it+1}^c}{\hat{\sigma}_{\varepsilon ct+1}}\right)$, where $\hat{\sigma}_{\varepsilon ct+1}^2$ is the estimator of the slope of the age profile for the asset disturbance term variance $\sigma_{\eta ct}^2$. Indeed, we propose to decompose the residual variance into age and cohort effects as follows:

$$\sigma_{\eta ct}^2 = \mu + \gamma_{ct} + \lambda_{at} + u_{ct},$$

where μ is a constant, γ_{ct} is a cohort effect, λ_{at} is an age effect, and u_{ct} is an error term which is supposed to be independent and identically distributed and of mean zero. Then, assuming that the cohort effect is time invariant as it should asymptotically be the case (Verbeek, 2008), we estimate the first difference (from *t* to *t+1*) of age effects—that is $\hat{\lambda}_{at+1} - \hat{\lambda}_{at}$—for each cohort in order to get $\hat{\sigma}_{\varepsilon ct+1}^2$.

Following the previous methodology, the estimation steps to obtain the vulnerability index can be summarized as follows:

- *Step 1.* Create a pseudo panel from repeated cross-section surveys. The rationale for this is to choose time-invariant characteristics to group households in each survey into cohorts.[24] The number of cells constituted equals the number of cohorts multiplied by the number of periods/surveys available for the analysis. Cell size

[24] A cohort is typically defined by the year of birth, education level and localization.

should be large enough in order to minimize the bias arising from using pseudo panel data and not genuine panel data.[25]

- *Step 2.* Estimate the residual variance of the logarithm of the asset index within each cell of the pseudo panel corresponding to cohort c at time t. Practically speaking, we regress for each cell at the household level the logarithm of the asset index on a set of variables (including gender dummy, age and age squared, education dummies, household size, number of children under 5 years old, urbanization dummy or localisation dummies) and estimate the residuals. The residual variance over cohorts corresponds to the variance of the residuals of the previous regression.

- *Step 3.* Regress the residual variance on cohort dummies and a polynomial function of age. Then, draw the estimated age effects on a graph to obtain the age-profile of the residual variance.[26] Estimate the slope of this age-profile for each cohort c which represents the estimated variance of the shocks faced by household, $\hat{\sigma}^2_{\varepsilon ct+1}$.

- *Step 4.* Draw a value $\tilde{\varepsilon}^c_{it+1}$ in the normal distribution with mean zero and variance $\hat{\sigma}^2_{\varepsilon ct+1}$ within each cohort c and combine it with the estimated coefficients of the observable characteristics to predict the vulnerability index $\hat{v}^c_{it}$ for each household i at time t belonging to cohort c. For that purpose, x^c_{it+1} can be predicted deterministically from x^c_{it} by incrementing age or assuming that characteristics are time invariant.

Creation of a Pseudo-Panel

In order to have a look at the dynamic of asset-poverty, we regroup households from the DHS into homogeneous cohorts: households whose heads have the same date of birth (we define five-year cohorts), the same level of education (no education, primary and secondary and more) and the same place of residence (ten departments and urban/rural distinction) are regrouped into cells. After regrouping some low-sized cells, 261 cells were constituted for each year of the DHS dataset, with an average size of around 150 households and 950 individuals in each cell.

Aggregate Estimates

Our estimates of the vulnerability index follow the different steps recalled previously. First, log per capita asset index is regressed on various household's characteristics such as log of household size, age of the head and its square, education and gender of the head, location and the presence of children under 5 years old. Residuals are

[25] As exposed by Verbeek and Nijman (1992), the bias in the standard within estimator based on pseudo panel data is decreasing with the number of individuals in each cell, more than with the number of cells. However, Verbeek (2008) notes that there is no general rule to judge whether cell size is large enough. Deaton (1985) also suggests that measurement error decreases as a function of the size of the cells.

[26] As in Deaton and Paxson (1994), we can normalize so that the fitted age effect at, for instance, age 35-40 equals the average residual variance of the logarithm of the asset index for 35-40 year-olds over all cohorts.

estimated from these regressions. Second, we calculate for each cell the variance of the residuals of the first-stage household-level regression. Third, we regress the residual variance on cohort dummies (created by crossing household head date of birth, education and location dummies) and a polynomial function of age (generally of two degrees or more if statistically significant). From the age profile of the residual variance, we calculate the slope which is an estimate of the variance of asset shocks. Note that this slope should necessary be positive (i.e. the amplitude of shocks grows with age) since the estimated variance should always be positive. This is generally the case. However, when it is not, contiguous cells have been regrouped for the estimates. Finally, once the variance of shocks is estimated for each cohort then the last estimation step consists in drawing values of shocks within the standard normal distribution and estimating the household vulnerability index using coefficient estimates.

Poverty and vulnerability rates are reported in Table 8 where a household is considered as poor when its asset index is below the 80th percentile of the 1995 distribution of asset index. An extremely poor household is one whose asset index is below the 40th percentile of the 1995 distribution of asset index. A household is considered as vulnerable if the probability to be poor or extremely poor is higher than 0.5, whereas it is considered as highly vulnerable for a probability higher than 0.8. At the national level, poverty headcount (71.5%) is not different from the estimated fraction of the population who is vulnerable to poverty. Moreover, 34.5% of the population is extremely poor, while is 34.7% vulnerable to extreme poverty. Whatever the threshold indeed, poverty and vulnerability do not appear very different from each other. If we look at non-poor people, 10.6% are vulnerable to poverty. Among the population that is vulnerable to poverty, 95.8% are poor, and among the vulnerable to extreme poverty, 85.7% are estimated to be extremely poor.

3.2.Poverty and Vulnerability Profiles

According to previous results, the characteristics of those who are estimated to be poor should not be very different from the characteristics of those who are estimated to be vulnerable to poverty. Table 9 presents the distribution of poor and vulnerable groups across various characteristics. We find clear similarities between the poor and the vulnerable. Indeed, poor and vulnerable groups are mostly rural. Relative to their share in the population (60.2%), rural households are over-represented among individuals who are poor (74.7%) or extremely poor (93.0%) and among those who are vulnerable to poverty (74.2%) or extreme poverty (91.9%). Other categories are over-represented among the poor and vulnerable groups: 41.8% of individuals live in a household where the head has no education, while 53.6% among the poor (77.3% among the extreme poor) and 53.5% among the vulnerable to poverty (74.7% among the vulnerable to extreme poverty). There are more malnourished children under 5 years old among the extremely poor (35.3%) or vulnerable to extreme poverty (34.9%) than in the whole population (23.2%). There are also less 5-11 year old children who attend school among the extremely poor (71.7%) or vulnerable to extreme poverty (72.6%) than in the whole population (83.4%). Interestingly, there are more lactating or pregnant women among the extremely poor (47.3%) or vulnerable to extreme poverty (45.9%) than in the whole population (34.6%).

When looking at the characteristics of the community, we find important discrepancies, since there are fewer extremely poor or vulnerable to extreme poverty with access to basic services like primary school (respectively 80.1% and 81.3% have access against 89.7% in the whole population), first cycle secondary school (respectively 13.4% and 14.9% have access against 39.1% in the whole population), second cycle secondary school (respectively 4.7% and 5.8% have access against 31.0% in the whole population), the market (respectively 12.7% and 14.8% have access against 40.8% in the whole population), hospitals (respectively 1.9% and 2.7% have access against 14.8% in the whole population), health centres (respectively 9.1% and 10.8% have access against 29.8% in the whole population), drugstores (respectively 21.7% and 22.9% have access against 37.2% in the whole population) and doctors' offices (respectively 2.2% and 3.5% have access against 28.6% in the whole population). Overall, we note that vulnerable people have access to basic services relatively more often than the poor, since some of them are actually non poor.

Table 7. Decomposition of changes in asset-based poverty between 1995 and 2005

Poverty line (perc. in 1995)	Headcount 1995	Headcount 2005	Headcount Change	Education: (Within) No or primary	Education: (Within) Secondary or more	Education: (Between)	Education: (Interaction) Crossed effect	Gender: (Within) Female head	Gender: (Within) Male head	Gender: (Between)	Gender: (Interaction) Crossed Effect	Children: (Within) Without under 5	Children: (Within) With under 5	Children: (Between)	Children: (Interaction) Crossed effect
20th	0.201	0.172	-0.028	-0.012	0.000	-0.017	0.001	0.001	-0.030	-0.003	0.003	-0.011	-0.014	-0.002	0.000
40th	0.400	0.339	-0.062	-0.029	-0.002	-0.032	0.002	0.000	-0.059	-0.008	0.005	-0.011	-0.044	-0.009	0.002
60th	0.600	0.513	-0.088	-0.040	-0.005	-0.043	0.001	-0.013	-0.071	-0.009	0.005	-0.017	-0.062	-0.012	0.002
80th	0.800	0.711	-0.089	-0.025	-0.021	-0.034	-0.009	-0.027	-0.057	-0.005	0.001	-0.027	-0.051	-0.010	0.000

Source: Own computations using DHS 1995, 2005

Table 8. Asset-poverty and vulnerability to asset-poverty

%	Number of individuals ('00,000)	Number of households ('00,000)	Fraction poor	Mean vulnerability to poverty	Fraction vulnerable to poverty	Fraction highly vulnerable to poverty	Fraction extremely poor	Mean vulnerability to extreme poverty	Fraction vulnerable to extreme poverty	Fraction highly vulnerable to extreme poverty
Overall	79.3	17.0	71.5	70.7	71.5	64.8	34.5	34.7	34.7	24.9
Non poor	22.6	6.8	0.0	13.3	10.6	3.2	0.0	0.3	0.0	0.0
Poor	56.7	10.2	100.0	93.6	95.8	89.3	48.3	48.4	48.5	34.8
Extremely poor	27.4	5.1	100.0	99.7	100.0	99.6	100.0	81.1	86.1	67.8
Non vulnerable to poverty	22.6	8.1	10.6	8.8	0.0	0.0	0.0	0.0	0.0	0.0
Vulnerable to poverty	56.7	11.5	95.8	95.3	100.0	90.5	48.3	48.4	48.5	34.8
Vulnerable to extreme poverty	27.5	7.0	100.0	100.0	100.0	100.0	85.7	87.0	100.0	71.7
Highly vulnerable to poverty	51.3	10.7	98.6	98.4	100.0	100.0	53.1	53.4	53.6	38.4
Highly vulnerable to extreme poverty	19.7	5.8	100.0	100.0	100.0	100.0	94.1	95.3	100.0	100.0

Source: Own computations using DHS

Table 9. Poor and vulnerable groups

	Overall		Non poor		Poor		Extremely poor		Vulnerable to poverty		Vulnerable to extreme poverty		Highly vulnerable to poverty		Highly vulnerable to extreme poverty	
	N ('00,000)	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Overall	79.3	100.0	22.6	100.0	56.7	100.0	27.4	100.0	56.7	100.0	27.5	100.0	51.3	100.0	19.7	100.0
Household and individual characteristics (from DHS 2005)																
Region																
West	12.0	15.1	3.1	13.8	8.9	15.6	4.1	15.1	9.0	15.9	4.5	16.4	8.1	15.7	3.2	16.2
Southeast	4.4	5.6	0.6	2.5	3.9	6.9	2.1	7.7	3.9	6.8	2.1	7.5	3.8	7.3	1.6	8.0
North	7.8	9.9	1.5	6.9	6.3	11.1	3.4	12.4	6.3	11.1	3.3	12.0	6.0	11.8	2.7	13.5
Northeast	2.7	3.4	0.5	2.1	2.2	3.9	1.1	4.1	2.2	3.9	1.2	4.2	2.1	4.0	0.9	4.4
Artibonite	12.9	16.3	2.4	10.8	10.5	18.5	5.0	18.4	10.3	18.2	4.9	17.7	9.4	18.4	3.5	17.7
Center	6.7	8.5	0.5	2.4	6.2	10.9	4.3	15.9	6.2	10.8	4.3	15.8	5.9	11.4	3.5	17.6
South	5.7	7.2	1.0	4.4	4.7	8.3	1.9	7.1	4.6	8.2	2.1	7.5	4.3	8.4	1.3	6.5
Grand-Anse	5.4	6.9	0.6	2.8	4.8	8.5	2.9	10.6	4.8	8.4	2.8	10.3	4.4	8.7	1.9	9.5
Northwest	4.7	6.0	0.7	3.0	4.1	7.2	2.3	8.3	4.0	7.0	2.1	7.7	3.6	7.0	1.2	6.2
Port-au-Prince	16.8	16.8	21.3	11.6	51.5	5.2	9.2	0.1	0.4	5.5	9.6	0.3	1.1	3.8	7.3	0.1
Area of residence																
Urbain	31.5	39.8	17.2	76.1	14.4	25.3	1.9	7.0	14.7	25.9	2.2	8.1	11.7	22.8	1.2	6.2
Rural	47.8	60.2	5.4	24.0	42.4	74.7	25.5	93.0	42.1	74.2	25.3	91.9	39.6	77.2	18.5	93.8
Head of households																
Male	45.6	57.5	11.7	51.6	33.9	59.8	16.5	60.4	33.8	59.6	16.6	60.4	30.8	60.0	11.6	58.9
Female	33.7	42.5	10.9	48.4	22.8	40.2	10.9	39.6	22.9	40.4	10.9	39.6	20.6	40.1	8.1	41.1
Education of head of household																
No education	33.1	41.8	2.8	12.2	30.4	53.6	21.2	77.3	30.3	53.5	20.6	74.7	29.4	57.2	16.6	84.1
Primary	37.7	47.5	13.1	58.1	24.5	43.3	6.2	22.7	24.6	43.5	6.9	25.1	20.8	40.5	3.1	15.9
Secondary and above	8.5	8.5	10.7	6.7	29.7	1.8	3.2	0.0	0.0	1.7	3.1	0.0	0.1	1.2	2.3	0.0
0-5 years old	10.3	13.0	2.3	10.1	8.1	14.2	4.2	15.4	8.0	14.2	4.2	15.3	7.3	14.3	3.0	15.4
Malnutrition (stunting)		1.0	23.2	0.1	9.4	0.9	27.4	0.6	35.3	0.9	27.2	0.6	34.9	0.8	28.4	0.4
Mortality		10.1		6.7		11.5		13.7		11.4		13.5		12.3		13.7

0-2 years old	4.2	41.1	0.9	40.4	3.3	41.3	1.7	41.4	3.3	41.4	1.7	41.3	3.0	41.2	1.3	41.4
Malnutrition (stunting)	0.4	21.4	0.0	9.7	0.3	24.5	0.2	27.9	0.3	24.0	0.2	30.1	0.3	24.4	0.2	29.4
Mortality		9.1		6.4		10.2		12.1		10.2		12.0		10.8		12.1
5-15 years old	21.1	26.6	4.3	19.1	16.8	29.6	8.6	31.3	16.7	29.4	8.4	30.6	15.3	29.9	6.0	30.4
Attend school	16.0	83.4	3.6	93.4	12.3	80.9	5.6	71.7	12.2	80.8	5.5	72.6	11.1	79.9	3.7	69.3
Do not attend school	5.2	16.6	0.7	6.6	4.5	19.1	3.0	28.3	4.4	19.2	2.9	27.4	4.2	20.1	2.3	30.7
5-11 years old	12.8	60.7	2.5	58.8	10.3	61.2	5.4	63.5	10.2	61.3	5.3	63.4	9.4	61.4	3.8	63.1
Attend school	8.7	79.8	2.0	94.4	6.7	76.3	3.0	65.8	6.6	76.4	3.0	66.7	6.1	75.3	2.0	63.3
Do not attend school	4.2	20.2	0.5	5.6	3.6	23.7	2.4	34.2	3.6	23.6	2.3	33.3	3.4	24.7	1.8	36.7
15-25 years old	16.2	20.5	5.4	24.1	10.8	19.1	4.4	16.1	11.0	19.3	4.6	16.7	9.7	18.8	3.1	15.5
25-50 years old	20.3	25.6	7.5	33.2	12.8	22.5	5.8	21.0	12.8	22.5	5.8	21.0	11.3	22.0	4.2	21.1
Female head	3.7	34.3	1.8	45.1	1.9	28.2	0.9	28.1	2.0	28.5	0.9	29.2	1.7	28.3	0.7	30.6
over 50 years old	11.3	14.3	3.1	13.5	8.3	14.6	4.4	16.2	8.3	14.7	4.5	16.4	7.7	15.1	3.5	17.6
over 60 years old	6.3	55.4	1.6	53.6	4.6	56.0	2.5	57.2	4.6	55.6	2.6	57.6	4.3	55.9	2.0	58.2
Monoparental	1.1	6.8	0.5	7.5	0.6	6.3	0.4	7.6	0.7	6.3	0.4	7.6	0.6	6.4	0.3	8.4
Female	1.0	84.1	0.5	89.5	0.5	79.8	0.3	80.8	0.5	79.8	0.3	78.7	0.5	79.7	0.3	78.6
Lactating and pregnant women	3.9	3.9	34.6	0.8	23.3	3.1	39.9	1.7	47.3	3.1	39.7	1.7	45.9	2.8	40.4	1.2
*Community characteristics (from DHS 2000)**																
Primary school																
With	71.1	89.7	19.4	96.2	51.7	87.4	20.1	80.1	50.7	87.2	18.7	81.3	44.4	86.1	12.1	80.3
Without	8.2	10.3	0.8	3.8	7.4	12.6	5.0	19.9	7.4	12.8	4.3	18.7	7.2	13.9	3.0	19.7
First cycle secondary school																
With	31.0	39.1	14.0	69.1	17.0	28.8	3.4	13.4	16.5	28.4	3.4	14.9	13.1	25.4	2.0	13.5
Without	48.3	60.9	6.2	30.9	42.1	71.2	21.7	86.6	41.6	71.6	19.6	85.1	38.4	74.6	13.1	86.5
Second cycle secondary school																
With	24.6	31.0	12.6	62.6	12.0	20.3	1.2	4.7	11.6	19.9	1.3	5.8	8.6	16.6	0.7	4.5
Without	54.7	69.0	7.6	37.4	47.1	79.7	23.9	95.3	46.6	80.1	21.7	94.2	43.0	83.4	14.4	95.5
Market																
With	32.3	40.8	15.0	74.1	17.4	29.4	3.2	12.7	16.8	28.9	3.4	14.8	13.1	25.4	2.0	13.2
Without	46.9	59.2	5.2	25.9	41.7	70.6	21.9	87.3	41.4	71.1	19.6	85.2	38.4	74.6	13.1	86.8
Hospital																
With	11.7	14.8	5.8	28.7	6.0	10.1	0.5	1.9	5.7	9.9	0.6	2.7	4.5	8.7	0.3	1.9
Without	67.6	85.2	14.4	71.3	53.1	89.9	24.6	98.1	52.4	90.1	22.4	97.3	47.0	91.3	14.8	98.1
Health Center																

	With	23.6	29.8	10.7	53.1	12.9	21.8	2.3	9.1	12.7	21.8	2.5	10.8	9.9	19.2	1.5	10.2
	Without	55.7	70.2	9.5	46.9	46.2	78.2	22.8	90.9	45.5	78.2	20.6	89.2	41.6	80.8	13.5	89.8
Drugstore																	
	With	29.5	37.2	11.2	55.3	18.3	31.0	5.4	21.7	18.0	30.9	5.3	22.9	14.8	28.7	3.2	21.3
	Without	49.8	62.8	9.0	44.7	40.8	69.0	19.6	78.3	40.2	69.1	17.8	77.1	36.8	71.3	11.9	78.7
Doctor's office																	
	With	22.7	28.6	12.6	62.3	10.1	17.1	0.6	2.2	9.8	16.8	0.8	3.5	7.0	13.5	0.4	2.3
	Without	56.6	71.4	7.6	37.7	49.0	82.9	24.5	97.8	48.4	83.2	22.3	96.5	44.6	86.5	14.7	97.7

Source: Own computations using DHS. Note: *community characteristics are available in 2000 not in 2005 in the DHS. Results are computed using sample weights.

4. POVERTY AND VULNERABILITY IN RURAL HAITI[27]

In order to fully characterize the determinants of poverty and vulnerability in rural Haiti, a unique survey can be used to assess the impact of idiosyncratic and covariate shocks on economic well-being (such as household consumption or income). This household survey on Haitian food security and vulnerability has been conducted in 2007 in rural areas. The number of households is around 3,000 distributed in 228 communities. It contains quantitative information on household consumption, production, income and assets as well as a good deal of qualitative information on perceived shocks, coping strategies, response capacity and other risks.

4.1.Methodology

Vulnerability to Shocks

In this section, we explore the relationships between consumption or income, on the one hand, and various idiosyncratic and aggregate covariates on the other hand. We suppose that households are imperfectly insured against shocks and have limited access to credit. So, assuming uninsured exposure to risk, we can write:

$$\ln y_{ij} = X_{ij}\beta + S_{ij}\gamma + S_{ij}\delta' X'_{ij} + \theta_j + \varepsilon_{ij}, \tag{1}$$

where y_{ij} is the consumption of household *i* in community *j*, X_{ij} is a vector of household characteristics, S_{ij} is a vector of observable shocks, θ_j is a community specific effect and ε_{ij} is the error term.

In the above equation, two parameters are of particular interest. First, we should assess whether γ is significantly different from zero that is whether observable shocks have significant impact on economic well-being. Second, in order to ascertain whether observable shocks have different impacts depending on household and community characteristics, we should also assess whether δ is significantly different from zero.

Community specific effect θ_j can be modelled either as a fixed effect or a random effect. In what follows, we will see how to model this unobservable component within a two-level linear random coefficient model. Finally, we should take into account the possibility that the error term ε_{ij} can be correlated with observable household characteristics and shocks so that parameters estimates might be biased.

Following Datt and Hoogeveen (2003), equation (1) parameters estimates are used to measure the impact of the observable shocks on poverty. First, the counterfactual welfare index (y^*_{ij}) is derived from the difference between actual consumption (y_{ij}) and the estimated impact of observable shocks that is:

[27] See Echevin, D. (2010b) for a complete version of this section.

$$y_{ij}^{*} = y_{ij} - [\exp(\ln \hat{y}_{ij}) - \exp(\ln \hat{y}_{ij} \mid S_{ij} = 0)]. \tag{2}$$

Second, we measure the impact of shocks on poverty by a *poverty gap* (*PG*):

$$PG = \Pr(\ln y_{ij} < \ln z) - \Pr(\ln y_{ij}^{*} < \ln z). \tag{3}$$

This poverty gap will inform us about the extent to which shocks affect poverty so that policy should be implemented to reduce the impact of shocks on social welfare.

Parameters estimates in equation (1) can be used as measures of vulnerability since they inform us about coping mechanisms. However, we don't learn much from these parameters about the variability of shocks, so we do not know their vulnerability incidence.

Vulnerability as Expected Poverty

One step further, we can define vulnerability to poverty as the probability of falling into poverty when one's consumption/income falls below a predefined poverty line. Furthermore, households will be considered as vulnerable when the probability to be poor in the future is below a chosen vulnerability threshold. In order to estimate such a probability, Chaudhuri *et al.* (2002) proposed to estimate the expected mean and variance in consumption using cross-sectional data or short panel data.

Let us define vulnerability for individual *i* in community *j* by:

$$\hat{v}_{ij} = \Pr(\ln y_{ij} < \ln z \mid X_{ij}) = \Phi\left(\frac{\ln z - \ln \hat{y}_{ij}}{\hat{\sigma}_{ij}}\right), \tag{4}$$

where $\Phi(.)$ denotes the cumulative density of the standard normal; *z* is the poverty line; $\ln \hat{y}_{ij}$ is the expected mean of log per capita consumption and $\hat{\sigma}_{ij}^2$ is the estimated variance of log per capita consumption.

As in Christiaensen and Subbarao (2005), the conditional mean and variance could be expressed from equation (1) as:

$$E\left(\ln y_{ij} \middle| X_{ij}\right) = X_{ij}\beta + E\left(S_{ij}\right)\left[\gamma + \delta' X_{ij}'\right] + E\left(\theta_j\right), \tag{6}$$

$$V\left(\ln y_{ij} \middle| X_{ij}\right) = \left[\gamma + \delta' X_{ij}'\right]' V\left(S_{ij}\right)\left[\gamma + \delta' X_{ij}'\right] + \sigma_\theta^2 + \sigma_\varepsilon^2. \tag{7}$$

One of the main strong points of Chaudhuri's approach resides in the fact that it is rather straightforward to implement on various types of datasets. One limitation of this approach when it is applied to a single cross-section is that it cannot take the temporal variability of parameters into account. Moreover, vulnerability estimates using cross-sections usually prove to rely on partial observation of the local covariate and idiosyncratic shocks experienced by households (*cf.*

Christiansen and Subbarao, 2005), which implies omitted variables or reverse causality biases. By taking into account both observable and unobservable shocks our approach thus build on previous literature by providing a larger spectra of possible shocks endured by households. What is more, a two-level modelling approach will allow us to assess the impact of shocks at a community level which is an appropriate level to analyse risk-sharing behaviours (*cf.* Suri, 2010).

A Multilevel Decomposition Analysis

Our methodological approach is based on a two-level linear random coefficient model where y_{ij} is the consumption of household *i* in community *j*, x_{ij} is a vector of household covariates (such as households characteristics, self-reported shocks and their interactions) and w_j is a vector of community covariates. One writes:

$$\begin{aligned} \ln y_{ij} &= \eta_{0j} + \eta_{1j} x_{ij} + u_{ij}, \\ \eta_{0j} &= \gamma_{00} + \gamma_{01} w_j + \zeta_{0j}, \\ \eta_{1j} &= \gamma_{10} + \gamma_{11} w_j + \zeta_{1j}, \end{aligned} \tag{8}$$

where the error term u_{ij} reflects unobserved heterogeneity of household consumption and the error terms ζ_{0j} and ζ_{1j} represent unobserved heterogeneity of consumption across communities. Given previous equations we get:

$$\ln y_{ij} = \gamma_{00} + \gamma_{01} w_j + (\gamma_{10} + \gamma_{11} w_j) x_{ij} + \zeta_{0j} + \zeta_{1j} x_{ij} + u_{ij}, \tag{9}$$

where the equation can be decomposed into a fixed part and a random part. For identification purposes, we assume that the covariates x_{ij} and w_j are exogenous with $E(\zeta_{0j} | x_{ij}, w_j) = 0$, $E(\zeta_{1j} | x_{ij}, w_j) = 0$ and $E(u_{ij} | x_{ij}, w_j, \zeta_{0j}, \zeta_{1j}) = 0$. This model can be estimated using standard statistical software such as Stata's *gllamm* command (Rabe-Hesketh and Skrondal, 2008).

In contrast with Günther and Harttgen (2009), we will both consider observable and unobservable shocks as sources of vulnerability, whereas Günther and Harttgen do not consider observable shocks in their analysis.

Using this multilevel random coefficient model, we can decompose the total conditional variance into two spatial levels: household and community. So, using equation (9) and following Chaudhuri *et al.* (2002), we estimate the expected unobservable idiosyncratic variance $\hat{\sigma}^2_{u_{ij}}$, covariate variance $\hat{\sigma}^2_{\varsigma_{0j}}$ and total variance $\hat{\sigma}^2_{u_{ij}+\varsigma_{0j}}$ of household consumption using the estimated coefficients from the following regressions:

$$\begin{aligned} u_{ij}^2 &= \alpha_0 + \alpha_1 x_{ij} + \alpha_2 w_j + \alpha_3 x_{ij} w_j, \\ \zeta_{0j}^2 &= \delta_0 + \delta_1 w_j, \\ (u_{ij} + \zeta_{0j})^2 &= \theta_0 + \theta_1 x_{ij} + \theta_2 w_j + \theta_3 x_{ij} w_j. \end{aligned} \tag{10}$$

Using variance estimates from the above equations, we will provide measures of vulnerability according to the different sources of vulnerability. First, we are concerned with vulnerability induced by structural (or permanent) poverty, that is the fraction of vulnerable households whose expected mean consumption $\ln \hat{y}_{ij}$ is already below the poverty line $\ln z$. Second, we will measure vulnerability induced by risk, that is the fraction of vulnerable households whose expected mean consumption $\ln \hat{y}_{ij}$ lies above the poverty line $\ln z$. As in Chaudhuri *et al.* (2002), a household is considered as vulnerable if the estimated vulnerability index is greater than the vulnerability threshold of 0.29.

Identification Issues

A problem associated with the estimation of equations (1) and (9) is that idiosyncratic and covariate observable shocks are potentially endogenous for at least three reasons. First, since the shocks are self-reported by the households in the questionnaire, it might be reported with errors. Hence, it is possible that households with a certain level of consumption or welfare consider an event to be a shock, while others with a different level of consumption or welfare may not. Second, if consumption levels influence the likelihood of exposure to the shock then reverse causality may arise. For instance, health shock has not the same probability of occurring depending on household consumption/income level. This problem is most likely to happen with idiosyncratic shocks. Community shocks are less likely to be influenced by household consumption or income. Third, shocks may be correlated to the error term because of unobserved heterogeneity. Unobserved factors may indeed influence both exposure to shocks and consumption/income. For example, richer households may better irrigate their lands. If irrigation is not observed, the estimated impact of drought on consumption declines may be upwardly biased.

These sources of estimation bias are difficult to take into account with cross-sectional data. However, as proposed in Datt and Hoogeveen (2003), a potential solution is the use of instrumental variables (IV) estimation. Instrumental variables are constructed as community means of shock variables leaving out the current household. These instruments are valid if households are more likely to report a shock when neighbours also report that shock, although neighbours affected by the shock do not influence other household's economic well-being in another way than through the household's self-reported shock.

4.2.Data

The vulnerability and food security survey was conducted in Haiti in October and November 2007 on approximately 3,000 households living in 228 rural communities. This survey has been realized by the National Coordination of Food Security Unit with the partnership of the World Food Program. A community-related component was added to the household component of the survey, in connection with infrastructures and accessibility to basic social services. So, this survey contains quantitative information on household consumption expenditures, production, income and assets as well as a good deal of qualitative information on perceived shocks, coping strategies and other hazards. Our empirical study will thus try to assess vulnerability by using both sets of data –quantitative and qualitative.

Prior to the 2010 earthquake, the rural population of Haiti represented about 60% of the total population. These households are particularly vulnerable to natural shocks such as droughts, floods and hurricanes. They also face other risks and shocks such as economic and health shocks, animal disease[28], crime and violence. When looking at the shocks faced by rural households in Haiti in Table 10, we find that many households face covariate shocks such as: increase in food prices, cyclones, floods, droughts and irregular rainfall; many of those shocks have an impact upon income or upon both income and assets, and less often upon assets only. On the other hand, among the worst shocks declared by the households, most of them are idiosyncratic shocks: they have to do with disease, casualties or death of a household member (for 42.5% of them) or animal diseases (14.0%); the worst covariate shocks are cyclones, floods, droughts and increase in food prices which concern around 26.3% of the households.

Table 11 presents summary statistics for variables used in the analysis. Consumption and income are expressed in Gourdes. The agricultural index is a composite indicator which is a linear combination of categorical variables obtained from a multiple correspondence analysis (*cf.* Asselin, 2009). Variables considered in the analysis are the number of lands, animals and agricultural materials owned by the household. The community index is a linear combination of community basic infrastructure and access to market variables (roads, access to elementary or secondary schools, health centres, markets, electricity and cell phone). A score of income diversity has also been built from the various income sources earned by the household. As four main income sources are declared by the household, the income diversity variable (*ID*) is defined as $ID_i = \frac{1}{2}\left(1 - \sum_{k=1}^{4}\left(s_i^k\right)^2\right)$, where s_i^k is the share of the kth income source in total income of household *i*. This score equals 0 when only one source of income is declared by the household. It averages 0.17 in the studied population.

As reported in Table 11, many heads of household are working in agricultural activities (54%) and about one quarter of them have no job. Another important source of income is trade. Note also that about three quarters of households are land owners.

[28] Haiti has had several covariate shocks on animal and plant diseases in recent history. However, declaration of households concerned here their own animals.

Table 10. Shocks in rural Haiti

%	% affected by this shock	Income only	Assets only	Both	% reporting this shock as the worst shock*	Income only	Assets only	Both
Increase in food prices	70.7	50.9	0.7	37.1	10.1	53.2	1.8	30.1
Cyclone, Flood	63.9	31.7	1.3	63.2	11.4	37.9	0.9	58.6
Drought	54.6	40.3	1.2	55.2	4.8	45.8	0.0	50.8
Irregular rainfall	49.6	37.9	0.3	56.7	1.7	27.3	2.3	63.6
Disease/Accident of a household member	47.6	42.0	1.1	54.1	30.8	41.2	1.0	51.8
Animal diseases	47.1	4.4	4.1	90.7	9.5	3.1	1.5	90.8
Crop diseases	37.6	45.1	0.5	51.6	4.5	38.8	0.9	54.3
Rarity of basic foodstuffs on the market	29.1	42.6	1.1	43.9	2.1	25.5	0.0	61.8
Increase in seed prices	27.7	48.5	0.8	42.0	1.0	51.9	0.0	29.6
Drop in relative agricultural prices	25.3	60.3	0.6	35.5	1.1	52.9	0.0	35.3
Drop in wages	22.6	48.6	0.6	47.9	1.6	25.5	0.0	63.8
Human epidemia	22.1	47.8	0.5	40.5	2.2	41.5	0.0	45.3
Death of an household member	21.9	33.0	0.4	63.3	11.7	30.6	0.7	64.2
Increase in fertilizer prices	12.9	43.9	1.0	44.5	0.9	56.3	0.0	31.3
Drop in demand	12.7	54.9	2.1	38.7	0.3	28.6	14.3	42.9
Insecurity (theft, kidnapping)	11.1	23.5	6.9	64.2	2.1	27.8	1.9	68.5
New household member	10.0	47.1	0.7	36.8	0.5	50.0	0.0	37.5
Cessation of transfers from relatives/friends	4.7	38.9	0.0	54.3	0.3	33.3	0.0	16.7
Loss of job or bankruptcy	3.9	39.0	1.5	57.6	0.9	35.0	0.0	50.0
Equipment, tool breakdown	2.7	49.7	1.6	27.5	0.0	100.0	0.0	0.0
Others	2.7	32.0	0.0	64.3	1.0	41.7	0.0	20.8

Source: Own computations using *Haitian Vulnerability and Food Security Survey*, 2007.
Notes: The sum of the three columns "income only", "assets only" and "both" do not sum to 100% due to non response or don't know or no impact. *Do not sum to 100% due to non response or don't know.

Table 11. Descriptive statistics

	Mean	SE
Household variables		
Log of consumption	7.30	1.06
Log of income	7.99	1.28
Agricultural index	0.24	0.13
Income diversity	0.17	0.13
Household size	5.2	2.3
Number of children	1.9	1.7
Age of head	49.8	16.4
Male head	0.71	0.45
Years of schooling (head)	2.6	3.8
Activity of head		
No job	0.23	0.42
Agroalimentary	0.54	0.50
Industry	0.03	0.18
Construction	0.00	0.05
Trade	0.12	0.33
Services	0.05	0.21
Other activity	0.03	0.17
Community variables		
Average years of schooling	4.0	1.6
Land owners	0.76	0.24
Community index	0.38	0.31

Source: Own computations using *Haitian Vulnerability and Food Security Survey*, 2007.

4.3.Results

Regression Results

We use self-reported shocks in order to estimate their impact on consumption and income. Table 12 presents OLS estimates and GLLAMM estimates. Both models are estimated with log consumption and log income. Our preferred specification regroups a large set of explanatory variables such as household characteristics, regional dummies, community characteristics, interaction between household characteristics and community characteristics, shocks variables, interaction between shocks variables and household characteristics, interaction between shocks variables and community characteristics. Estimating the two-level linear random coefficient model (GLLAMM) allows us to decompose the variance of the residuals into an idiosyncratic variance and a covariate variance.

Table 12. Regression results

	Consumption (in log)						Income (in log)					
	OLS				GLLAMM		OLS				GLLAMM	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Intercept	7.79	0.00	8.94	0.00	9.09	0.00	7.44	0.00	7.80	0.00	7.56	0.00
Household variables												
Agricultural index	-0.37	0.66	-0.12	0.89	-0.16	0.91	1.30	0.18	1.50	0.13	1.18	0.22
Number of adults over 50 years	-0.17	0.00	-0.10	0.06	-0.09	0.52	-0.13	0.03	-0.09	0.18	-0.08	0.19
Number of adults 25-50 years	-0.10	0.04	-0.04	0.47	-0.03	0.54	-0.10	0.09	-0.05	0.40	-0.05	0.39
Number of adults 15-24 years	-0.03	0.46	0.03	0.50	0.04	0.54	-0.07	0.16	-0.03	0.58	-0.03	0.57
Number of children 12-14 years	0.01	0.87	0.07	0.19	0.08	0.65	-0.12	0.03	-0.08	0.19	-0.07	0.25
Number of children 6-11 years	0.03	0.33	0.01	0.91	0.01	0.97	-0.04	0.19	-0.02	0.87	-0.02	0.84
Number of infants 3-5 years	0.03	0.36	0.00	0.99	0.00	1.00	-0.03	0.46	0.00	0.97	-0.01	0.96
Number of infants 0-2 years	-0.01	0.80	-0.01	0.89	-0.02	0.92	-0.05	0.24	-0.02	0.88	-0.02	0.84
Age of head	0.01	0.06	0.01	0.54	0.01	0.64	0.02	0.05	0.02	0.18	0.01	0.26
Age of head^2/100	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.03	0.00	-0.02	0.00
Male head	0.00	0.93	-0.02	0.79	-0.04	0.55	0.12	0.06	0.15	0.04	0.14	0.05
Years of schooling of head	0.04	0.00	-0.02	0.49	-0.02	0.65	0.04	0.00	0.06	0.13	0.05	0.19
No job	0.16	0.02	0.16	0.03	0.14	0.59	0.16	0.05	0.17	0.04	0.16	0.07
Income diversity	0.25	0.00	0.33	0.06	0.34	0.30	0.57	0.00	0.64	0.00	0.60	0.00
Land owner	-0.09	0.62	-0.76	0.14	-0.68	0.51	0.05	0.80	-0.13	0.83	0.07	0.90
Region												
North West	-0.16	0.35	-0.27	0.14	-0.30	0.72	-0.37	0.06	-0.28	0.18	-0.33	0.13
North	-0.35	0.09	-0.39	0.08	-0.37	0.75	-0.02	0.93	0.27	0.31	0.25	0.35
North East	-0.98	0.00	-0.91	0.00	-0.90	0.22	-0.27	0.22	-0.23	0.35	-0.19	0.44
Artibonite	-0.31	0.03	-0.33	0.05	-0.36	0.30	0.31	0.06	0.31	0.12	0.29	0.16
Centre	-0.84	0.00	-0.63	0.00	-0.64	0.02	-0.13	0.54	-0.15	0.53	-0.17	0.50
West	0.13	0.42	0.03	0.87	-0.02	0.95	0.49	0.01	0.57	0.01	0.57	0.01
Grande'Anse	-0.85	0.00	-0.74	0.00	-0.79	0.45	-0.81	0.00	-0.68	0.00	-0.72	0.00
Nippes	-0.17	0.30	-0.11	0.58	-0.11	0.64	-0.07	0.72	-0.05	0.84	0.04	0.86
South	0.34	0.02	0.24	0.15	0.19	0.58	0.10	0.55	0.21	0.29	0.09	0.68
Southeast	ref		ref		ref		ref		ref		ref	
Community variables												
% Land owners	0.33	0.38	0.47	0.60	0.27	0.90	1.24	0.00	1.32	0.20	1.68	0.14
Community index	-0.17	0.17	-0.60	0.22	-0.55	0.77	-0.09	0.50	-0.72	0.21	-0.49	0.49
Average years of schooling	0.06	0.07	0.06	0.06	0.06	0.51	0.03	0.38	0.06	0.15	0.04	0.27
*Household * Community variables*												

Average years of schooling * Agricultural index	0.17	0.08	0.20	0.04	0.20	0.24	0.01	0.92	0.02	0.89	0.04	0.70
Average years of schooling * Number of children	0.00	0.55	0.00	0.92	0.00	0.87	0.00	0.88	0.00	0.91	0.00	0.89
% Land owner * Agricultural index	-1.03	0.12	-1.44	0.04	-1.45	0.17	-2.11	0.01	-2.32	0.01	-2.05	0.01
% Land owner * Household size	-0.04	0.19	-0.10	0.01	-0.10	0.49	-0.11	0.00	-0.17	0.00	-0.16	0.00
% Land owner * Age of head	0.01	0.09	0.01	0.41	0.01	0.56	0.01	0.18	0.00	0.95	0.00	0.71
Community index * Agricultural index	0.60	0.19	0.48	0.31	0.54	0.31	0.54	0.31	0.45	0.42	0.41	0.45
<u>*Shock variables*</u>												
Idiosyncratic health shock	-1.31	0.00	-3.17	0.00	-3.18	0.27	-1.66	0.00	-4.13	0.00	-4.12	0.00
Idiosyncratic disease shock	-0.64	0.12	-0.18	0.83	-0.25	0.93	-1.34	0.00	-1.70	0.09	-1.63	0.11
New household member	1.72	0.03	6.33	0.01	5.51	0.61	3.54	0.00	8.57	0.00	8.46	0.00
Loss of income	0.12	0.76	-2.19	0.02	-1.88	0.38	0.08	0.86	-0.04	0.97	-0.64	0.57
Covariate climate shock	0.25	0.35	-0.51	0.55	-0.62	0.70	0.27	0.37	1.70	0.08	1.78	0.08
Covariate health shock	-1.43	0.02	-3.75	0.03	-3.40	0.71	-1.40	0.04	-1.79	0.36	-0.96	0.66
Covariate economic shock	-0.53	0.12	0.04	0.97	-0.13	0.97	-0.34	0.39	-1.55	0.23	-1.09	0.44
Insecurity shock	-0.59	0.08	-2.20	0.10	-2.15	0.76	-0.47	0.22	-2.16	0.16	-2.18	0.16
<u>*Shock * Household variables*</u>												
Idiosyncratic health shock * Nb adults 15 and more			-0.07	0.51	-0.07	0.53			0.04	0.73	0.04	0.75
Idiosyncratic health shock * Age of head			-0.01	0.62	0.00	0.77			0.00	0.92	0.00	0.88
Idiosyncratic health shock * Years of schooling of head			0.07	0.15	0.07	0.16			0.02	0.72	0.04	0.45
Idiosyncratic health shock * Income diversity			-0.07	0.71	-0.05	0.87			0.19	0.39	0.28	0.20
Idiosyncratic health shock * Land owner			0.64	0.21	0.60	0.55			-0.23	0.70	-0.30	0.62
Idiosyncratic disease shock * Nb adults 15 and more			0.30	0.00	0.30	0.00			0.33	0.00	0.32	0.00
Idiosyncratic disease shock * Age of head			-0.01	0.35	-0.01	0.28			-0.01	0.39	-0.01	0.26
Idiosyncratic disease shock * Years of schooling of head			0.03	0.41	0.02	0.75			-0.04	0.25	-0.04	0.26
Idiosyncratic disease shock * Income diversity			-0.48	0.00	-0.47	0.00			-0.16	0.35	-0.11	0.52
Idiosyncratic disease shock * Land owner			0.85	0.10	0.80	0.63			0.58	0.33	0.46	0.44
New household member * Nb adults 15 and more			0.16	0.40	0.14	0.64			0.21	0.32	0.26	0.23
New household member * Age of head			-0.04	0.10	-0.03	0.46			-0.03	0.22	-0.03	0.26
New household member * Years of schooling of head			-0.21	0.04	-0.22	0.21			-0.11	0.34	-0.11	0.36
New household member * Income diversity			-0.77	0.07	-0.81	0.17			-1.53	0.00	-1.48	0.00
New household member * Land owner			0.31	0.80	0.21	0.87			2.60	0.07	3.12	0.03
Loss of income * Nb adults 15 and more			0.03	0.73	0.07	0.87			0.02	0.86	0.04	0.73
Loss of income * Age of head			0.03	0.00	0.03	0.01			0.01	0.34	0.01	0.27
Loss of income * Years of schooling of head			0.03	0.56	0.02	0.68			-0.02	0.71	-0.01	0.76
Loss of income * Income diversity			0.32	0.10	0.35	0.32			0.02	0.93	0.03	0.90
Loss of income * Land owner			0.50	0.27	0.50	0.32			-0.72	0.17	-0.50	0.35
Covariate climate shock * Nb adults 15 and more			-0.16	0.12	-0.19	0.38			-0.22	0.06	-0.22	0.06
Covariate climate shock * Age of head			0.01	0.15	0.02	0.54			0.00	0.90	0.00	0.94
Covariate climate shock * Years of schooling of head			-0.03	0.48	-0.02	0.78			-0.03	0.44	-0.04	0.39
Covariate climate shock * Income diversity			0.54	0.00	0.52	0.34			0.13	0.53	0.12	0.57

Covariate climate shock * Land owner		-0.71	0.10	-0.71	0.61		1.02	0.04	1.06	0.04
Covariate health shock * Nb adults 15 and more		0.06	0.71	0.02	0.95		-0.05	0.80	-0.02	0.92
Covariate health shock * Age of head		0.03	0.04	0.03	0.12		0.01	0.63	0.01	0.64
Covariate health shock * Years of schooling of head		0.04	0.60	0.04	0.60		-0.08	0.34	-0.10	0.23
Covariate health shock * Income diversity		0.61	0.05	0.62	0.07		0.90	0.01	0.68	0.07
Covariate health shock * Land owner		0.54	0.49	0.55	0.62		-0.27	0.77	0.11	0.91
Covariate economic shock * Nb adults 15 and more		-0.03	0.83	0.02	0.85		-0.08	0.56	-0.10	0.48
Covariate economic shock * Age of head		0.00	0.98	0.00	0.85		0.02	0.27	0.01	0.31
Covariate economic shock * Years of schooling of head		0.06	0.25	0.05	0.35		0.07	0.21	0.07	0.20
Covariate economic shock * Income diversity		-0.30	0.15	-0.32	0.13		-0.26	0.29	-0.23	0.34
Covariate economic shock * Land owner		0.48	0.37	0.56	0.33		-0.84	0.16	-1.21	0.05
Insecurity shock * Nb adults 15 and more		0.14	0.23	0.15	0.37		-0.03	0.82	-0.01	0.94
Insecurity shock * Age of head		0.01	0.30	0.02	0.30		0.02	0.08	0.03	0.07
Insecurity shock * Years of schooling of head		-0.02	0.77	-0.01	0.90		-0.04	0.55	-0.03	0.60
Insecurity shock * Income diversity		-0.33	0.20	-0.32	0.66		-0.18	0.55	-0.25	0.40
Insecurity shock * Land owner		-1.58	0.01	-1.60	0.28		-0.81	0.27	-0.82	0.26
*Shock * Community variables*										
Idiosyncratic health shock * % Land owners		2.45	0.01	2.50	0.02		2.46	0.03	2.48	0.04
Idiosyncratic health shock * Community index		0.01	0.98	-0.15	0.83		0.46	0.44	0.33	0.62
Idiosyncratic disease shock * % Land owners		-1.11	0.11	-1.16	0.66		-0.03	0.97	-0.04	0.96
Idiosyncratic disease shock * Community index		-0.30	0.47	-0.30	0.61		-0.29	0.56	-0.36	0.48
New household member * % Land owners		-1.30	0.55	-0.90	0.91		-1.59	0.53	-2.99	0.25
New household member * Community index		-2.57	0.04	-2.49	0.05		-1.90	0.18	-2.09	0.16
Loss of income * % Land owners		-0.43	0.64	-0.77	0.69		-0.88	0.40	-0.46	0.68
Loss of income * Community index		0.47	0.40	0.47	0.67		0.70	0.28	1.07	0.12
Covariate climate shock * % Land owners		-0.14	0.86	0.07	0.98		-2.40	0.01	-2.71	0.01
Covariate climate shock * Community index		0.64	0.21	0.62	0.57		0.97	0.10	0.96	0.13
Covariate health shock * % Land owners		-1.16	0.44	-1.27	0.92		-2.25	0.19	-2.93	0.14
Covariate health shock * Community index		0.57	0.52	0.80	0.51		0.88	0.39	0.78	0.54
Covariate economic shock * % Land owners		-0.21	0.84	-0.03	1.00		2.20	0.08	2.04	0.14
Covariate economic shock * Community index		0.22	0.73	0.18	0.94		-0.46	0.53	-0.71	0.42
Insecurity shock * % Land owners		3.17	0.01	2.81	0.53		2.03	0.14	1.85	0.18
Insecurity shock * Community index		-0.10	0.89	-0.05	0.98		0.23	0.78	0.46	0.60
Idiosyncratic variance				0.69	0.00				0.92	0.00
Covariate variance				0.03	0.93				1.69	0.02
Number of households	2585	2585		2585		2612	2612		2612	
Number of communities	228	228		228		228	228		228	
R2 or Pseudo-R2	0.32	0.36		0.92		0.36	0.38		0.91	

Source: Own computations using *Haitian Vulnerability and Food Security Survey*, 2007.

In the regressions, shocks variables were regrouped into broad categories: idiosyncratic health shocks (disease/accident or death of a household member), idiosyncratic disease shocks (animal and crop diseases), new household member, loss of income (drop in wages, cessation of transfers from relatives/friends, loss of job or bankruptcy, equipment/tool breakdown), covariate climate shocks (cyclone, flood, drought and irregular rainfall), covariate health shocks (human epidemia), covariate economic shocks (increase in food prices, rarity of basic foodstuffs on the market, increase in seed prices, drop in relative agricultural prices, increase in fertilizer prices, drop in demand), health shocks (human epidemia), insecurity shocks (theft, kidnapping).

In Table 12, OLS estimates without shocks interacting with characteristics shows the mean impact of shocks. Their impact is generally negative except when hosting new household members (positive impact). In particular, idiosyncratic and covariate health shocks have large and significant negative effects on both consumption and income.

Regression results in Table 12 also help us characterizing vulnerable groups by differentiating the impact of shocks on well-being according to different household and community characteristics.

Idiosyncratic health shocks. The negative impact of this shock is reduced in absolute term when many households own lands in the community. This may be due to the fact that idiosyncratic health shock can be mutually insured within richer communities.

Idiosyncratic disease shocks. The significant positive parameter on the number of more than 15 years old household members shows that the idiosyncratic disease shock concerning crops or animals significantly increases the productivity of adults who may have to compensate for this kind of losses. In other words, the presence of a larger number of 15+ year old has a positive effect in reducing the impact from an animal/plant disease shock. Furthermore, idiosyncratic disease shock significantly decreases the benefits of income diversity for household economic well-being.

New household member. On the one hand, the positive impact of accommodating a new member in the household is reduced when the head of the household is higher educated or for greater diversity of income. The positive impact also decreases with the community index (access to basic infrastructures). On the other hand, the household benefit more from a new member in case of land ownership.

Loss of income. The negative impact of a loss of income appears to be significantly reduced when the head of the family is older.

Covariate climate shocks. The negative impact of covariate climate shock is significantly reduced with income diversity. The impact of this shock is further negative when many households own lands in the community.

Covariate health shocks. The negative impact of covariate health shock is significantly reduced when the household owns a land and when the head is older.

Covariate economic shocks. The negative impact of aggregate economic shock is significantly reduced when the household owns a land.

Insecurity shocks. The negative impact of insecurity shock is significantly increased in absolute term when the household owns a land. The impact of this shock is significantly less negative when many households own lands in the community.

Simulation Results

Previous estimates of equation (9) with GLLAMM are used to simulate the impact of self-reported idiosyncratic and covariate shocks on both poverty and vulnerability. Table 13 presents the results. We define two poverty thresholds: one is chosen so that 80% of the households are poor; another one is chosen so that 40% are considered as *extremely* poor. What is more, a household is considered as vulnerable if the estimated vulnerability index is greater than the vulnerability threshold of 0.29. People are thus considered as vulnerable to poverty when they are more likely to fall into poverty in any period over two consecutive periods than to not be poor, that is $(1-P)^2 \leq 0.5$, where P is the probability to fall below the poverty line. So, previous condition can be rewritten as $P \geq 0.29$.

For simulation purposes, the poverty line is chosen so that 80% (resp. 40%) of households have *expected* mean consumption/income below it. As a result, mean vulnerability appears to be respectively 63% and 46% for consumption and 67% and 45% for income. Using a vulnerability threshold of 0.29, vulnerability rates are respectively 98% and 87% for consumption and 96% and 76% for income.

Simulations exercises first consist in estimating the poverty rate and the vulnerability rate without observable idiosyncratic shocks (column 2 in Table 13) or without covariate shocks (column 3). As reported in Table 12, shocks which have the largest impact on consumption and income are health shocks, be they household or community shocks. So, most of the impact of observable shocks could be attributed to these particular shocks. On the contrary, loss of income has very little impact on poverty and vulnerability to poverty.

Without observable idiosyncratic shocks (column 2 in Table 13), the consumption-poverty rate falls to 28% and the consumption-extreme poverty rate is estimated to be 6%. So, the poverty gap, as it is defined by equation (3), corresponds to 52 percentage points, whereas the extreme poverty gap is 34 percentage points. Without observable covariate shocks, poverty decreases less: the poverty gap is 10 percentage points and the extreme poverty gap is 11 percentage points.

We also simulate the impact of observable shocks on the vulnerability rates. This impact is twofold: observable shocks have an impact on the mean (as stated in equation (6)) as well as on the variance of consumption/income (as stated in equation (7)). On the one hand, the percentage of households with mean consumption/income below the poverty line is what we call poverty induced vulnerability. On the other hand, the percentage of households with mean consumption/income above the poverty line that would fall into poverty due to consumption/income variability is what we call risk induced vulnerability.

Simulations results of the impact of shocks on vulnerability are as follows. Firstly, the impact of observable idiosyncratic shocks (in particular, observable idiosyncratic health shocks) on the vulnerability rate is large, whereas covariate shocks have little impact on it. Without observable idiosyncratic shocks, the rate of vulnerability to poverty (resp. to extreme poverty) is estimated to be 64% (resp. 28%), compared to 98% (resp. 87%) with these shocks, which represents a 34 percentage points (resp. 58 percentage points) fall. Without observable covariate shocks, the rate of vulnerability to poverty (resp. extreme poverty) is estimated to be 95% (resp. 73%), compared to 98% (resp. 87%) with these shocks, which represents a 3 percentage points (resp. 14 percentage points) fall. We also have simulated the impact of idiosyncratic and covariate observable shocks on household income. The results are very similar to previous ones (see Table 13).

Secondly, Table 13 shows that observable idiosyncratic and covariate shocks have larger impact on the mean than on the variance of consumption/income. This is particularly true when considering observable idiosyncratic shocks. Indeed, the ratio between poverty induced and risk induced vulnerability that equals 4.42 with shocks is sharply decreased in the absence of observable shocks. This ratio is even lower without observable idiosyncratic shocks (0.35) than without observable idiosyncratic shocks (0.77). So, one possible interpretation of those results is that the main impact of shocks is to increase poverty permanently rather than transitorily.

Finally, one should estimate the impact of unobservable idiosyncratic or covariate shocks on vulnerability. By construction, unobservable shocks have no impact on mean consumption or mean income. However, they influence the variability of both consumption and income. So, we estimate vulnerability rates using either unobservable shocks or observable shocks as sources of consumption/income variability. Table 13 indicates that unobservable idiosyncratic shocks have more influence on households' vulnerability than unobservable covariate shocks. Indeed, 96% of households are vulnerable to unobservable idiosyncratic shocks (80% when considering vulnerability to extreme poverty), whereas they are 82% to be vulnerable to unobservable covariate shocks (44% when considering vulnerability to extreme poverty). By contrast, observable idiosyncratic shocks have the same influence on households' vulnerability than observable covariate shocks. Indeed, the ratio of idiosyncratic to covariate vulnerability is 1.00 (1.04 when considering vulnerability to extreme poverty) for observable shocks, whereas it is 1.17 (respectively 1.83) for unobservable shocks.

Table 13. Vulnerability decomposition and simulations

	Consumption			Income		
	Factual (1)	Without idiosyncratic shocks (2)	Without covariate shocks (3)	Factual (1)	Without idiosyncratic shocks (2)	Without covariate shocks (3)
Poverty rate*	0.80	0.28	0.70	0.80	0.24	0.63
Mean vulnerability	0.63	0.39	0.58	0.67	0.33	0.57
Vulnerability rate**	0.98	0.64	0.95	0.96	0.46	0.86
Poverty induced vulnerability	0.80	0.28	0.70	0.80	0.24	0.63
Risk induced vulnerability	0.18	0.36	0.25	0.16	0.22	0.23
Poverty induced/Risk induced vulnerability	4.42	0.77	2.75	5.11	1.10	2.70
Idiosyncratic vulnerability (unobserved)	0.96	0.60	0.94	0.92	0.41	0.83
Covariate vulnerability (unobserved)	0.82	0.30	0.73	0.82	0.27	0.67
Idiosyncratic/Covariate vulnerability (unobserved)	1.17	2.01	1.28	1.12	1.56	1.22
Idiosyncratic vulnerability (observed)	0.91	0.00	0.84	0.89	0.00	0.77
Covariate vulnerability (observed)	0.91	0.39	0.00	0.90	0.32	0.00
Idiosyncratic/Covariate vulnerability (unobserved)	1.00	-	-	1.00	-	-
(Extreme) Poverty rate*	0.40	0.06	0.29	0.40	0.06	0.24
Mean vulnerability	0.46	0.23	0.41	0.45	0.16	0.34
Vulnerability rate**	0.87	0.28	0.73	0.76	0.17	0.54
Poverty induced vulnerability	0.40	0.06	0.29	0.40	0.06	0.24
Risk induced vulnerability	0.47	0.22	0.44	0.36	0.11	0.30
Poverty induced/Risk induced vulnerability	0.85	0.29	0.66	1.10	0.60	0.82
Idiosyncratic vulnerability (unobserved)	0.80	0.27	0.69	0.66	0.15	0.47
Covariate vulnerability (unobserved)	0.44	0.07	0.32	0.45	0.08	0.28
Idiosyncratic/Covariate vulnerability (unobserved)	1.83	3.79	2.16	1.47	1.93	1.68
Idiosyncratic vulnerability (observed)	0.62	0.00	0.50	0.58	0.00	0.40
Covariate vulnerability (observed)	0.60	0.11	0.00	0.56	0.10	0.00
Idiosyncratic/Covariate vulnerability (observed)	1.04	-	-	1.03	-	-

Source: Own computations using *Haitian Vulnerability and Food Security Survey*, 2007.

Notes: *The poverty line is chosen so that 80% (resp. 40%) of households have expected mean consumption below it. The poverty rate is the percentage of households whose expected mean consumption is below the poverty line. **The vulnerability threshold is 29%.

5. POST-EARTHQUAKE CHARACTERIZATION OF ASSET-WEALTH[29]

5.1.Data Sources and Methodology

A post-earthquake food security-oriented survey was conducted in June 2010 by the CNSA in collaboration with its main partners (ACF, FEWS-Net, Oxfam GB, FAO, UNICEF and WFP). The sampling used for the household survey is a probabilistic cluster method, using two stages: (i) enumeration sections (geographical areas) and camps and (ii) households. 2003 census data is used to select the enumeration sections, with a probability proportional to population size. Eight households are then selected randomly in each section. Camps are selected using the International Organization for Migration (IOM) data; the number of camps selected was proportional to the size of the communes. The sampling method yielded 1901 interviewed households, located in the disaster areas (camp and non-camp sites) as well as in some non-directly affected areas. Geographic strata covered by the EFSA II survey are presented in Figure 2.

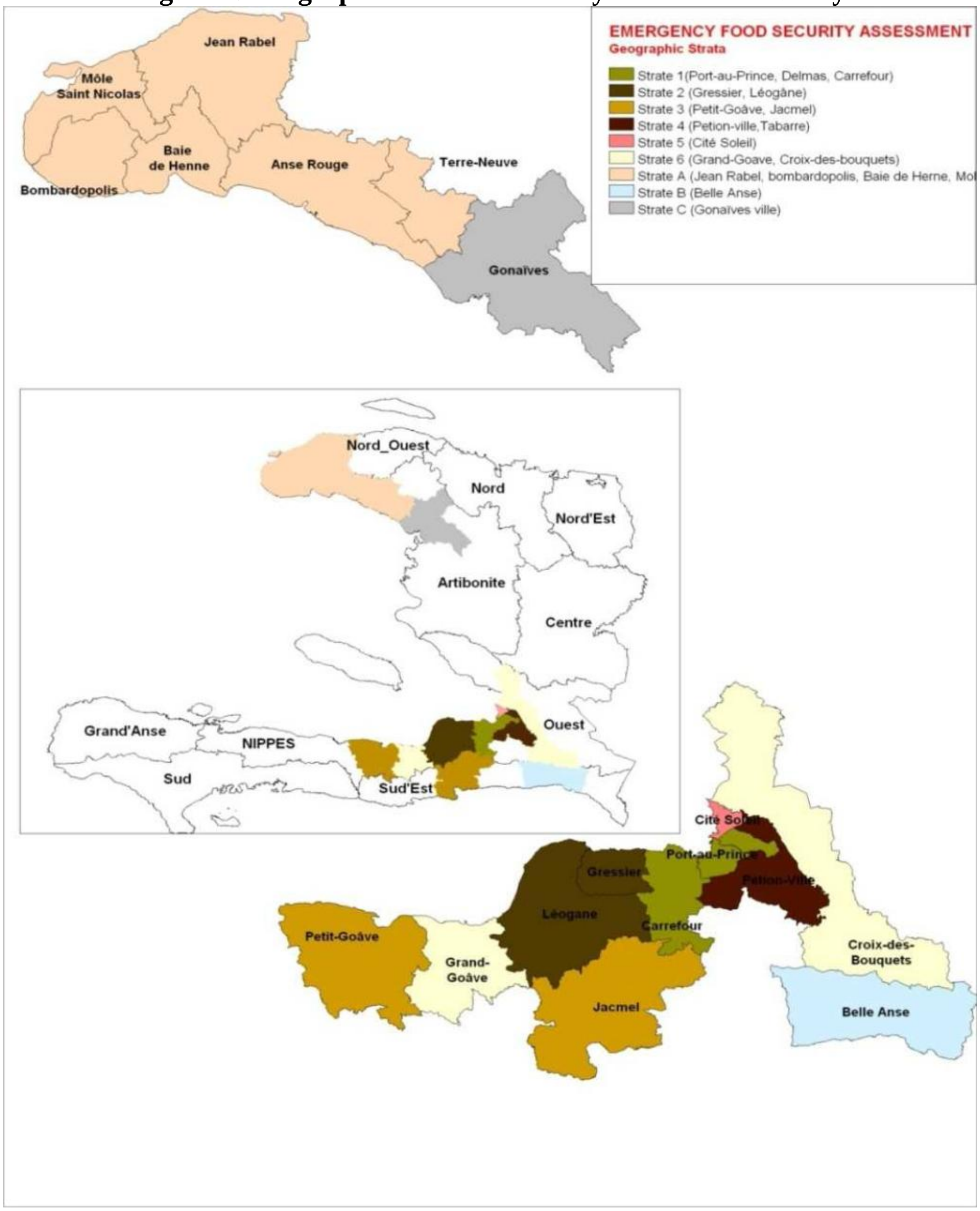
To randomly select households, different methods were used for the urban households, the rural households and the camps. For urban households, survey investigators observe and mark the location of households on a street map that does not contain socio-economic infrastructure, and the households are randomly selected. For rural households, previously mapped buildings are randomly selected using enumeration section maps, and households living in those buildings are interviewed; if there are no households inside, then the closest household is selected. For camps, survey investigators start from the centre of the camp and walk towards the outside in a different randomly selected paths. They number each household encountered in the way, and randomly select two households to interview. For all three types of sampling, when multiple households are found living in the same building or tent, a single household is randomly selected.

5.2. Assets

Based on the June survey, an asset index is calculated using a wider set of pre-earthquake dichotomous variables, namely some durable goods not declared in the February survey and access to basic utilities. Table 14 reports both weights and contributions to inertia. Weights have signs consistent with interpretation of the first component as an asset-poverty index. In directly affected areas, contribution to inertia of lighting appears to be particularly high (26.7%). Water source also contributes in a large extent to inertia (18.9%). Having tools or material for fishery, agricultural production and handicraft contributes to 12.2% of the inertia explained by the first component of the analysis. Other items contribute to less than 10% of inertia each.

[29] This section is an excerpt from Echevin (2011).

Figure 2. Geographic strata covered by the EFSA II survey



Source: CNSA (2010b).

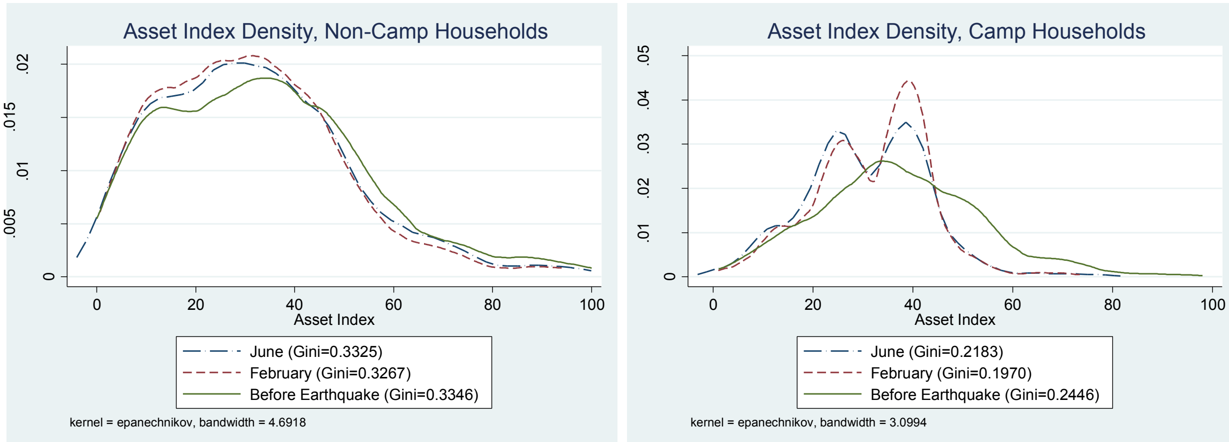
Table 14: Asset index weights

Variable	Directly affected areas Weight	Directly affected areas Inertia (%)	Non-directly affected areas Weight	Non-directly affected areas Inertia (%)
Water Source				
Tap water	-0.494	0.055	-0.802	0.075
Private water	0.845	0.122	1.093	0.092
Well water	-0.511	0.013	0.615	0.021
Water Filtration				
Filtration product*	-0.354	0.025	-0.294	0.009
Rudimentary method	0.102	0.000	-0.057	0.000
Cooking Fuel	-0.232	0.026	-0.234	0.021
Lighting				
Electricity	0.405	0.049	1.094	0.131
Lamp	-1.273	0.218	-0.803	0.166
Toilet				
Latrine	-0.134	0.007	0.221	0.010
WC	1.467	0.095	1.391	0.017
Oven	1.369	0.086	1.066	0.006
Heater	0.003	0.000	0.196	0.009
Hot water tank	-0.133	0.009	-0.235	0.020
Television	0.402	0.050	1.112	0.115
Radio	0.102	0.004	0.411	0.029
Cell phone	0.018	0.000	0.113	0.003
Bicycle	0.215	0.003	0.933	0.039
Motorcycle	0.373	0.004	1.04	0.026
Flatiron	0.155	0.008	0.172	0.006
Fan	0.597	0.069	1.359	0.093
Car	1.092	0.029	0.758	0.007
Sewing machine	0.308	0.004	0.555	0.012
Tools/Material	-0.951	0.122	-0.588	0.090
Small business stocks	0.089	0.001	0.068	0.001
Partial inertia contribution (%)	14.78		19.16	

Source: Own computations using June 2010 (EFSA II) surveys. Note: *Filtration products are generally used in relatively poor regions so that it can explain the negative weight.

Using retrospective data on assets from the June survey, Figure 4 presents the asset index distributions before the earthquake, in February and in June. Using this index, we can notice that the inequality of household wealth (as measured by the Gini coefficient) has decreased after the earthquake due to higher losses among the wealthiest. This is particularly true among households living in camps (Gini is 0.2446 before the earthquake and 0.1970 in February). Then, between February and June, inequality of household wealth has increased—from 0.3267 to 0.3325 among non-camp households and from 0.1970 to 0.2183 among camp households.

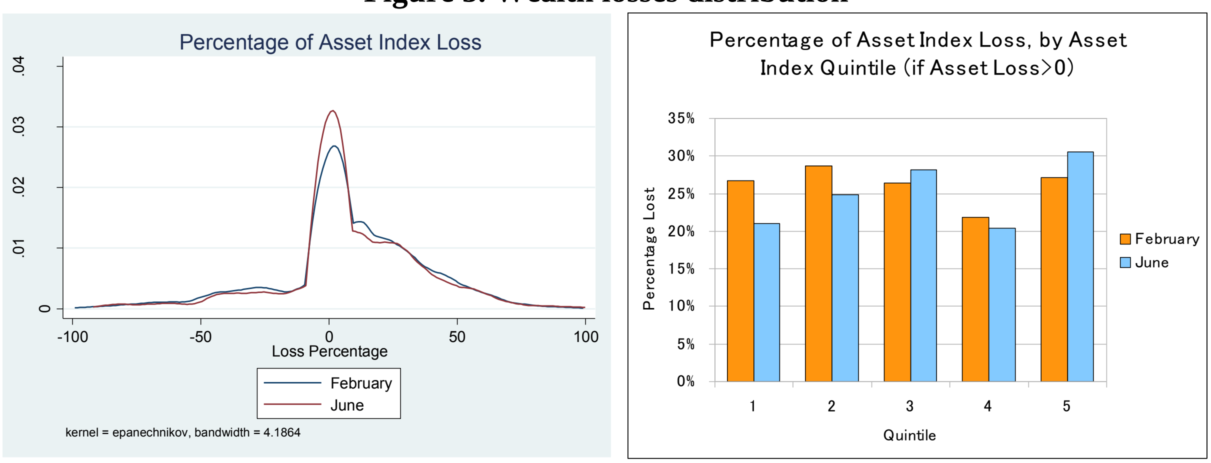
Figure 4. Distribution of wealth



Source: Own computations using June 2010 (EFSA II) surveys. Notes: The sample is restricted to the households residing in the six strata that cover areas directly affected by the earthquake. Weights are calculated using pre-earthquake assets.

Figure 5 presents the distribution of wealth losses in percentage of pre-earthquake wealth. The percentage of asset loss among households who lost assets is around 25%. This percentage does not seem to vary a lot according to wealth quintile.

Figure 5. Wealth losses distribution



Source: Own computations using June 2010 (EFSA II) surveys. Notes: The sample is restricted to the households residing in the six strata that cover areas directly affected by the earthquake. Asset index weights are calculated using pre-earthquake assets.

5.3.Directly Affected Areas

Table 15 presents descriptive statistics for households living in affected areas. The food consumption score is calculated based on the number of different food groups consumed by the household, to represent diversity, and the number of times a week they are consumed. Notably, we observe that the average food consumption score is 55.79, with a standard deviation of 19.75. A majority of households is above the limit food consumption thresholds (the limit consumption threshold being 42 and the critical threshold being 26).

Table 15 also shows that, in June, 44% of the households in affected areas had received assistance and that 32% had received food assistance. 37% of the respondents' houses were partially or totally destroyed, making it impossible to live in them. 44% of the households slept in their homes, while 44% slept in a camp. 12% of the households had agricultural production as their main source of income, 37% had trade, 26% unqualified work, 17% professional work and 3% lived mostly out of transfers. Aid was received from both abroad (12%) and from within Haiti (18%).

Table 15. Descriptive statistics

	Mean	Std
Food consumption score	55.79	19.75
Assistance	0.44	0.50
Food assistance	0.32	0.47
Housing not damaged	0.17	0.37
Housing damaged but still usable	0.46	0.50
Housing partially destroyed	0.11	0.32
Housing totally destroyed	0.26	0.44
Sleeping in the house	0.44	0.50
Sleeping beside the house	0.09	0.29
Sleeping in the neighborhood	0.27	0.44
Sleeping in the commune	0.18	0.38
Sleeping outside the commune	0.02	0.14
Sleeping in a camp	0.44	0.50
Main income source before the earthquake		
Agricultural production	0.12	0.32
Trade	0.37	0.48
Unskilled work	0.26	0.44
Skilled work	0.17	0.38
Transfer	0.03	0.18
Other income source	0.04	0.19
Aid/transfers from abroad	0.12	0.32
Aid/transfers from Haiti	0.18	0.38

Source: Own computations using June 2010 (EFSA II) surveys. Note: The sample is restricted to the households residing in the six strata that cover areas directly affected by the earthquake.

5.4.Pre-Earthquake Conditions

Table 16 presents summary statistics by quintile of pre-earthquake wealth. The poorest households lived mostly in the East of the affected area (Léogane, Gressier, Jacmel, Petit Goâve, Grand Goâve and Croix-des-Bouquets). They were mostly agricultural households: 66% of them were practicing agriculture, compared to only 5% among the wealthiest, who were mostly concentrated in Port-au-Prince or Pétionville. The poorest households lived in houses with no electricity and no toilets, and do not have access privately to water. They had no car and no oven for cooking. Only few of them had a TV or a fan. Most (66%) had tools or materials for production. Compared to other groups, they took more part in associations be they religious ones (28%) or not (19%). In the population, very few people (around 1% to 2%) were part of cash and food for work programs. Participants represented only 0.8% among the poorest households. The poorest households derived their main source of income from agriculture production (38%), trade (30%) and unskilled work (20%). They received comparatively less aid from relatives or friends from Haiti (11%) or from abroad (14%) than the richest (resp. 29% and 23%).

Table 16. Households characteristics before the earthquake, by pre-earthquake quintile of wealth

Pre-earthquake quintile of wealth	Poorest	2	3	4	Richest
Number of households	250	259	239	254	244
Location (commune)					
Carrefour, Port-au-Prince and Delmas	0.04	0.10	0.21	0.24	0.30
Léogane, Gressier	0.28	0.24	0.16	0.11	0.07
Jacmel, Petit Goâve	0.31	0.16	0.13	0.06	0.08
Pétionville, Tabarre	0.03	0.12	0.15	0.23	0.32
Cité Soleil	0.03	0.15	0.21	0.31	0.18
Grand Goâve, Croix-des-Bouquets	0.32	0.22	0.14	0.06	0.05
Household size (median)	6	5	6	5	5
Housing characteristics					
Electricity (lighting)	0.03	0.48	0.70	0.82	0.90
Toilet (WC)	0.00	0.00	0.01	0.06	0.37
Private water	0.00	0.06	0.13	0.63	0.86
Oven ownership	0.00	0.01	0.01	0.05	0.38
Television ownership	0.09	0.41	0.74	0.82	0.96
Fan ownership	0.04	0.14	0.41	0.47	0.85
Car ownership	0.00	0.03	0.01	0.02	0.17
Tools/Materials for production	0.66	0.34	0.09	0.14	0.08
Number of poultry owned (median)	7	9	6	5	8
Number of goats owned (median)	3	3	4	2	3
Number of swines owned (median)	2	3	3	3	4
Number of cattle owned (median)	1	2	2	1	2
Number of sheeps owned (median)	2	8	2	2	-
Number of horses/donkeys owned (median)	1	1	1	2	1
Take part in cash-for-work program	0.008	0.015	0.017	0.016	0.00
Take part in food-for-work program	0.008	0.008	0.008	0.008	0.00
Take part in religious association (June)	0.28	0.32	0.24	0.22	0.24
Take part in non religious association (June)	0.19	0.08	0.10	0.08	0.10
Agricultural practice	0.66	0.32	0.13	0.06	0.05
Income sources					
Agricultural production	0.38	0.15	0.04	0.02	0.00
Trade	0.30	0.32	0.40	0.43	0.42
Unskilled work	0.20	0.33	0.30	0.28	0.17
Skilled work	0.08	0.16	0.17	0.17	0.30
Transfer	0.02	0.01	0.04	0.04	0.05
Other income source	0.02	0.02	0.05	0.06	0.05
Transfer sent to relatives/friends in Haiti	0.14	0.17	0.25	0.26	0.29
Transfer received from relatives/friends in Haiti	0.11	0.11	0.20	0.22	0.23
Transfer received from relatives/friends abroad	0.14	0.12	0.15	0.21	0.34

Source: Own computations using June 2010 (EFSA II) surveys. Notes: The sample is restricted to the households residing in the six strata that cover areas directly affected by the earthquake.

5.5.Damages and Losses due to the Earthquake

Table 17 presents households damages and losses by pre-earthquake wealth quintile. Many households in the affected areas appear to have had their house damaged or destroyed (82.6% of all households). Concerning income sources, the richest households appear to have more experienced the death of one or more income earners (11.5%) compared to other groups (8.7% on average for all households). They have also experienced loss of savings more often. Compared to other households, the richest ones have lost more: in February 2010, 86.5% experienced assets losses, compared to only 17.6% among the poorest. The main assets lost were a television, radio or fan among the richest; they concerned a radio, cell phone and iron among the poorest. In June 2010, many of the richest households had recovered from the pre-earthquake situation (16.0%), whereas the poorest households were more to lose. This feature of the dynamics of poverty may indicate the existence of a *poverty trap*: the poorest households keep losing more and more after the disaster, whereas the richest households manage to recover. From these figures, what is important to know yet is how the richest households have recovered, whereas the poorest have not. Is it actually the case that assistance might not have been allocated in an equal and unbiased way? Or, were the richest households more able to cope with the disaster?

Table 17. Damages and losses due to the earthquake, by pre-earthquake quintile of wealth

Pre-earthquake wealth quintile	Number of households	Housing			Income		
		% Not damaged	% Damaged, but still usable	% Partially or totally destroyed and not usable	% Death of income earner	% Loss of income earner	% Lost their savings
Poorest	250	24.4	42.4	32.4	5.6	11.2	14.0
2	259	10.8	43.2	45.9	8.1	26.6	20.1
3	239	14.2	43.5	38.9	9.6	27.6	21.8
4	254	15.7	49.2	35.0	8.7	19.3	27.6
Richest	244	17.6	49.6	32.4	11.5	25.8	30.7
Total	1246	16.5	45.6	37.0	8.7	22.1	22.8

Pre-earthquake wealth quintile	Number of households	Assets				Agricultural assets*	
		% Assets losses (June) (1)	% Assets losses (February) (2)	Variation (1) – (2)	Main assets lost (February)	% Agric. assets losses (June)	Main agric. assets lost (June)
Poorest	250	19.6	17.6	-2	Radio, cell phone, iron	12.1	Poultry, goats, swine, cattle
2	259	39.0	38.2	-0.8	Television, radio	22.2	Poultry, swine
3	239	57.3	51.9	-5.4	Television, radio	31.8	Poultry, swine
4	254	74.0	79.5	5.5	Television, radio	6.7	Poultry, swine
Richest	244	70.5	86.5	16	Television, radio,	0.0	Poultry, goats

					fan		
Total	1246	51.9	54.6	2.6	Television, radio	15.8	Poultry, goats, swine

Source: Own computations using June 2010 (EFSA II) surveys. Notes: The sample is restricted to the households residing in the six strata that cover areas directly affected by the earthquake. *Among households practicing agriculture before the earthquake.

REFERENCES

Alderman, H., Hoddinott, J., and B. Kinsey (2002), "Long term consequences of early childhood malnutrition," mimeo, FCND, International Food Policy Research Institute, Washington D.C.

Asselin, L-M. (2009), Analysis of multidimensional poverty: Theory and case studies. Springer.

Behrman, J., Alderman, H., and J. Hoddinott (2004), "Hunger and malnutrition," in Global Crises, Global Solutions, B. Lomborg (ed.). Cambridge (UK): Cambridge University Press.

Benzécri, J.P. (1973), L'analyse des données 2 : L'analyse des correspondances. Paris: Dunod.

Booysen F., van der Berg, S., von Maltitz, M., and G. du Rand (2008), "Using an asset index to assess trends in poverty in seven sub-Saharan African countries," World Development, 36(6), 1113-1130.

Bourguignon, F., and C. Goh (2004), "Trade and labor vulnerability in Indonesia, Republic of Korea, and Thailand," in Kharas, H., and K. Krumm (eds), East Asia integrates: a trade policy agenda for shared growth. World Bank and Oxford University Press, Washington DC.

Carroll, C. (1992), "The buffer-stock theory of saving: Some macroeconomic evidence," Brookings Papers on Economic Activity, 23 (2), 61-156.

Carter, M. R., and C. B. Barrett (2006), "The economics of poverty traps and persistent poverty: An asset-based approach," Journal of Development Studies, 42 (2), 178–199.

Chaudhuri S., Jalan, J., and A. Suryahadi (2002), "Assessing household vulnerability to poverty from cross-sectional data: a methodology and estimates from Indonesia," Discussion Paper 0102-02, Department of Economics, Columbia University.

Christiaensen, L., and K. Subbarao (2001), "Towards an understanding of vulnerability in rural Kenya," mimeo, TheWorld Bank: Washington DC

CNSA (2007), Analyse compréhensive de la sécurité alimentaire et de la vulnérabilité en milieu rural Haïtien. République d'Haïti.

CNSA (2010a), Évaluation rapide d'urgence de la sécurité alimentaire post-séisme : Haiti. March 2010.

CNSA (2010b), Follow-up emergency food security assessment (EFSA II): Summary and findings. September 2010.

Datt, G. and H. Hoogeveen (2003), "El Niño or El Peso? Crisis, poverty and income distribution in the Philippines," World Development, 31(7), 1103-1124.

Deaton, A. (1985), "Panel data from time series of cross-sections," Journal of Econometrics, 30(1-2), 109–26.

Deaton, A. (1991), "Saving and liquidity constraints," Econometrica, 59 (5), 1221– 1248.

Deaton, A., and C. Paxson (1994), "Intertemporal choice and inequality," Journal of Political Economy, 102 (3), 437-467.

De Ferranti, D., Perry, G. E., and L. Serven (2000), Securing our Future in a Global Economy. World Bank, Washington DC.

Dercon, S. (1998) Wealth, risk and activity choice: cattle in Western Tanzania. *Journal of Development Economics*, 55, 1-42.

Echevin, D. (2010a), "Vulnerability to asset-poverty in sub-Saharan Africa," *mimeo*, Université de Sherbrooke.

Echevin, D. (2010b), "Characterizing poverty and vulnerability in rural Haiti: A multilevel decomposition approach," *mimeo*, The World Bank.

Echevin, D. (2011), "Livelihoods and the allocation of emergency assistance after the Haiti earthquake," *mimeo*, The World Bank.

Elbers, C., Lanjouw, J. O., and P. Lanjouw (2003), "Micro-level estimation of poverty and inequality," Econometrica, 71 (1), 355-364.

Fafchamps, M., Udry, C., and K. Czukas (1998), "Drought and saving in West Africa: Are livestock a buffer stock?" Journal of Development Economics, 55 (2), 273-305.

Filmer, D., and L. H. Pritchett (2001), "Estimating wealth effects without expenditure data—or tears: An application to educational enrollments in states of India," Demography, 38 (1), 115-132.

Günther, I. and K. Harttgen (2009), "Estimating households vulnerability to idiosyncratic and covariate shocks: A novel method applied in Madagascar," World Development, 37(7), 1222-1234.

Hoddinott, J. (2006), "Shocks and their consequences across and within households in rural Zimbabwe," Journal of Development Studies, 42 (2), 301-321.

Kazianga, H., and C. Udry (2006), "Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso," Journal of Development Economics, 79 (2), 413-446.

Kolbe A.R., R.A. Huston, H. Shannon, E. Trzcinskib, B. Miles, N. Levitz, M. Puccio, L. James, J.R. Noel and R. Muggah (2010), "Mortality, crime and access to basic needs before and after the Haiti earthquake: a random survey of Port-au-Prince households," Medicine, Conflict and Survival 26 (4), 281-297.

Morduch, J. (1994), "Poverty and vulnerability," American Economic Review, Papers and Proceedings, 84 (2), 221-225.

Morduch, J. (1995), "Income smoothing and consumption smoothing," Journal of Economic Perspectives, 9 (3), 103-114.

Morduch, J., and G. Kamanou (2004), "Measuring vulnerability to poverty," in Insurance Against Poverty, S. Dercon (ed.). Oxford University Press.

Moser, C. (1998), "The asset vulnerability framework: Reassessing urban poverty reduction strategies," World Development, 26(1), 1–19.

Moser C. and A. Felton (2007). "The Construction of an Asset Index Measuring Asset Accumulation in Ecuador," The Brookings Institution, CPRC Working Paper 87, pp 1 - 20.

OCHA (2010), Haiti Humanitarian Appeal. February 2010.

OCHA (2011), Bulletin humanitaire. February 2011.

Pedersen, J., and K. Lockwood (2001), “Determination of a poverty line for Haiti,” Fafo Institute of Applied International Studies Working Paper.

Pritchett, L., Suryahadi, A., and S. Sumarto (2000), “Quantifying vulnerability to poverty: A proposed measure, applied to Indonesia,” World Bank Social Monitoring and Early Response Unit.

Rabe-Hesketh, S. and A. Skrondal (2008), Multilevel and longitudinal modeling using Stata. Stata Press.

Ravallion, M., amd M. Huppi (1991), “Measuring changes in poverty: a methodological case study of Indonesia during an adjustment period,” World Bank Economic Review, 5, 57-82.

Rosenzweig, M., and H. Wolpin (1993), “Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: investment in bullocks in India,” Journal of Political Economy, 101 (2), 223-244.

Sahn, D. E., and D. C. Stifel (2000), “Poverty comparisons over time and across countries in Africa,” World Development, 28 (12), 2123–2155.

Sahn, D. E., and D. C. Stifel (2003), “Urban–rural inequality in living standards in Africa,” Journal of African Economies, 12 (4), 564–597.

Stifel, D. C, and L. Christiaensen (2007), “Tracking poverty over time in the absence of comparable consumption data,” World Bank Economic Review, 21 (2), 317-341.

Tarozzi, A., and A. Deaton (2009), “Using census and survey data to estimate poverty and inequality for small areas,” Review of Economics and Statistics, 91 (4), 773–792.

Verbeek, M., and T. Nijman (1992), “Can cohort data be treated as genuine panel data?,” Empirical Economics, 17(1), 9–23.

Verbeek, M. (2008), “Pseudo-panels and repeated cross-Sections,” *Advanced Studies in Theoretical and Applied Econometrics*, 46(2), 369-383.

World Bank (2006), Haiti country economic memorandum: Options and opportunities for inclusive growth. The World Bank, Washington DC.

World Bank (2007), Social Resilience and State Fragility in Haiti. The World Bank, Washington DC.

Zimmerman, F. J., and M. R. Carter (2003), “Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints,” Journal of Development Economics, 71 (2), 233-260.